

ABSTRACT

Title of Dissertation: HERD BEHAVIOR IN VOLUNTARY
 DISCLOSURE DECISIONS: AN EXAMINATION
 OF CAPITAL EXPENDITURE FORECASTS

Nerissa Christine Brown, Doctor of Philosophy, 2005

Dissertation Directed By: Professor Lawrence A. Gordon
 Department of Accounting and Information
 Assurance

Professor Russell R. Wermers
Department of Finance

This study documents behavior consistent with herding in voluntary disclosure decisions and investigates two possible reasons for this phenomenon. Based on theories of social learning and rational herds, herding in disclosure decisions may be due to managers' use of information reflected in the past disclosure decisions of other firms (informational herding), and/or managers' incentives to maintain or build a good reputation with investors (reputational herding). Employing a duration model for repeated events, I analyze the timing of capital expenditure forecasts for a broad sample of disclosing and nondisclosing firms. Results show that a firm's propensity to release capital expenditure forecasts is positively associated with the proportion of prior disclosing firms within its industry, thus, supporting arguments of herding. This association is significantly higher for less capital-intensive firms and firms operating

in highly competitive industries which suggests that incentives to herd are greater for firms facing relatively high competition. To further distinguish between informational and reputational herding, I investigate whether the tendency to herd varies with the content and precision of other firms' forecasts, and with the level of managerial reputation. As predicted, I find that a firm's propensity to disclose increases with the precision of peer firms' forecasts and when peer forecasts signal a decrease in capital expenditures. Also, I find that herding is greater for managers that are comparably less reputable. Overall, the results confirm the existence of herd behavior in capital expenditure forecast decisions and that the behavior is driven partly by informational and reputational incentives. Extensive sensitivity analyses confirm the robustness of these results.

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by

Nerissa Christine Brown

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2005

Advisory Committee:

Professor Lawrence A. Gordon, Co-Chair
Professor Russell R. Wermers, Co-Chair
Professor Martin P. Loeb
Professor Partha Sengupta
Professor John C. Chao

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Dedication

To my dear mother, Millicent Russell-Brown; my sister, Janelle Brown; and my grandmother, Doris Russell. Your love, inspiration, encouragement, and unwavering support were a constant source of strength during my studies. The completion of this dissertation would not have been possible without you.

Acknowledgements

I would like to thank the members of my dissertation committee, Dr. Lawrence Gordon (Co-chair), Dr. Russell Wermers (Co-chair), Dr. Martin Loeb, Dr. Partha Sengupta, and Dr. John Chao, for their suggestions, comments, numerous reviews, and support. My utmost gratitude goes to Dr. Lawrence Gordon for his continuous guidance and support throughout my doctoral process. Also, very special thanks to Dr. Russell Wermers for invaluable insights on herd behavior and duration analysis.

I would like to thank Tashfeen Sohail for his review of earlier drafts of this document and numerous discussions of the STATA[®] software. Thanks also to Pramod Pillai, Mary Shum, and Omar Asghar for their assistance in the data collection process.

Finally, I would like to thank Dr. Carmelita Troy, Dr. Kristina Minnick, Dr. April Knill, Dr. Nevena Koukova, and my fellow Ph.D. students at the Robert H. Smith School of Business for their friendship and support.

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Chapter 1

Introduction

Prior studies of disclosure trends and anecdotal evidence from the business press¹ suggest “wave-” or “herd-like” patterns in voluntary disclosure decisions. While substantive theoretical arguments for herding in voluntary disclosure decisions exist, there is scant empirical evidence to either support or refute these hypotheses. More importantly, there is no empirical work on the underlying sources of herding in voluntary disclosures. Consequently, the main objectives of this study are: 1) to empirically document evidence consistent with herding in voluntary disclosure decisions, and 2) to investigate the incentives for this behavior.

Herding is broadly defined to include any similarity or convergence in behavior brought about by the interaction of individuals or firms (Hirshleifer and Teoh 2003). Theories of social learning and rational herds provide two possible expla-

¹ In December 2004, energy companies Burlington Northern Santa Fe and Norfolk Southern announced their 2005 capital expenditure budgets within a few days of each other (*Reuters*, December 2, 2004; *PR Newswire*, December 2, 2004). Also, in 2001 many airlines successively released warnings of slumping revenues and earnings (*Dow Jones News Service*, June 19, 2001). A similar trend is evident in recent disclosures of accounting misstatements and errors. For example, in October 2003, A T & T Corp. announced an understatement of its 2001 and 2002 expenses just a few days after its rival Qwest Communications announced a restatement of its 2000 and 2001 results (*Reuters*, October 21, 2003).

nations for why firms may choose to disclose in herds.² First, managers may make use of private information reflected in the past disclosure decisions of presumably better-informed managers and consequently choose to disclose (termed informational herding; see Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992; Welch 1992). Second, managers may follow the disclosure decisions of more reputable managers in order to influence investors' assessment of their abilities (termed reputational herding; see Scharfstein and Stein 1990).³

While patterns of herding are evident in various types of disclosures, I choose to focus on capital expenditure forecasts for the following reasons: First, disclosures of future capital expenditures carry high strategic costs because they signal a firm's growth opportunities to rivals or potential market entrants. Given these costs, firms may have incentives to withhold such information and disclose only when peer firms have released similar information (Chamley and Gale 1994; Dye and Sridhar 1995; Jorgensen and Kirschenheiter 2003). I, therefore, expect herding to be prevalent for forward-looking capital expenditure information. Second, prior research shows that capital expenditure disclosures are a relevant signal of firm value and reputation (e.g., Chung, Wright, and Charoenwong 1997; McConnell and Muscarella 1985). Consequently, I expect herding in capital expenditure disclosure decisions to be driven in part by reputational incentives.

In addition, forecasting business investment continues to be of keen interest to

² Managers may randomly converge in their disclosure decisions simply because they have similar information to disclose and have similar private information of the net benefits of disclosure. While such random convergence has been termed herding in the literature, this study is primarily concerned with herding due to interactions or interdependencies between firms' disclosure decisions.

³ This study presumes that only managers with privately held information face the disclosure decision. It does not presume that managers will fabricate information for disclosure if none is received.

policymakers, academics, and business economists. Such interest has increased in recent years as conservative business capital spending has been a major factor in both the recent recession and the subsequent slow expansion of the U.S. economy.⁴ Therefore, focusing on capital expenditure forecasts creates the opportunity to provide timely evidence of the interaction of forecast releases among firms and its implications for gauging economy-wide spending.

Using a conditional variance-corrected duration model for repeated events, I analyze the timing of capital expenditure forecast decisions for 1981 disclosing and nondisclosing firms over 8 quarters ending in the third quarter of 2001. Theories of herding argue that the tendency to make similar decisions increases with the number of firms taking the same action. Consistent with this argument, I find that firms' propensity to release capital expenditure forecasts is positively associated with the proportion of disclosing firms within their industry. This association is significantly higher for less capital-intensive firms and firms operating in highly competitive industries, thus suggesting that incentives to herd are greater for firms facing relatively high competition. I further investigate the underlying incentives to engage in herd behavior and find that the use of information reflected in past disclosure decisions as well as managerial concerns for reputation are both key factors of herding in capital expenditure forecasts.

Overall, the results support arguments of herding in voluntary disclosure decisions and suggest that firms are employing a wait-and-see approach when deciding whether or not to disclose relevant information. Moreover, the results suggest that poorly informed managers and less reputable managers disclose with the herd in order to gain informational and reputational advantages.

⁴ In his July 20, 2004 semiannual testimony, Federal Reserve Chairman Alan Greenspan said that corporate America's investment in fixed capital continues to fall short of cash flow even though the economy is rebounding.

I also conduct additional analyses to enrich my results. Given that firms may disclose multiple forecasts across a single disclosure period, I re-estimate the results separately for each forecast event. While this procedure results in efficiency losses, I find that the tendency to herd is relatively stable across initial and revised forecast events. Next, I use two alternative fixed effects regressions to control for unobserved factors which may be independently driving firms within the same industry to converge in their disclosure decisions. The results remain reliable and consistent with expectations, thus ruling out random convergence as an alternative explanation. Last, series of sensitivity analyses show that the results are robust to alternative measurements of key variables and the inclusion of additional control variables.

This study contributes to the voluntary disclosure and the rational herding literatures in three ways. First, I provide previously undocumented evidence of herd behavior in the voluntary disclosure of capital expenditure forecasts. This finding strongly support the existence of interdependence among firms' disclosure practices. Such interdependence is either ignored or treated as exogenous in prior empirical work. Second, I provide evidence that both informational and reputational incentives are key sources of herding in disclosure decisions. This is in contrast to most empirical studies of herding which examine only one or none of these two incentives. Third, the study employs an empirical procedure which is more suitable for studying disclosure events. The conditional duration model takes into consideration that a firm's disclosure choice is influenced by its prior disclosure choices and thus, is well suited for examining multiple firm disclosures. Moreover, unlike traditional discrete choice models, the conditional duration model allows the probability of disclosure to vary across time and across forecast events.

This study has several practical implications as it highlights the need for firms to put in place mechanisms that will induce managers to disclose value-relevant infor-

mation on a timely basis rather than in response to the disclosure decisions of other firms. Such mechanisms can be in the form of better contracting practices and/or corporate governance structures. For instance, recent studies show that corporate governance structures such as boards and audit committees are positively associated with both the quality and frequency of voluntary disclosures (see Ajinkya, Bhojraj, and Sengupta 2005; Karamanou and Vafeas 2005). Since better corporate governance increases disclosure forthcomingness, it can be argued that better governance reduces incentives to delay disclosure so as to gain informational and/or reputational advantages from disclosing with the herd.

The remainder of this dissertation is organized as follows: chapter 2 discusses the relevant literature; chapter 3 develops the hypotheses; the research methodology is presented in chapter 4; chapter 5 details the data and sample selection procedures, and provides descriptive evidence; and chapter 6 presents the empirical analysis. Chapter 7 presents a series of sensitivity analyses, and chapter 8 provides concluding remarks.

Chapter 2

Literature Review

2.1 Studies of voluntary disclosures

Theoretical studies of voluntary disclosure, assuming credible disclosures and zero disclosure costs, suggest full disclosure of information will occur due to investors' belief that nondisclosing firms have the worst possible information (Grossman 1981; Milgrom 1981). In the presence of fixed positive disclosure costs, only firms whose information implies economic benefits above these costs will disclose (Verrecchia 1983). In the literature, the benefits of disclosure are often argued to include capital market benefits resulting from reduced information asymmetries. Specific capital market benefits include increased stock valuation and liquidity in equity markets, increased interest from institutional investors and financial intermediaries, and lower costs of external financing (Diamond and Verrecchia 1991; Lang and Lundholm 1993, 1996; Welker 1995; Botosan 1997; Sengupta 1998; Healy, Hutton, and Palepu 1999; Easley and O'Hara 2004). Disclosure costs primarily include information production and dissemination costs, the strategic consequences of disclosing commercially valuable information to competitors (Darrough and Stoughton 1990; Gigler 1994), and the potential costs of legal or regulatory actions (Dye 1985).

In addition to valuation related benefits, self-interested managers may disclose private information in order to influence investors' assessment of their ability (Trueman 1986). In this study, managerial ability is defined to include not only the aptitude for decision-making but also managerial foresight and performance (Holmstrom and Ricart i Costa 1986; Sridhar 1994). Therefore, voluntary disclosures signal managers' good judgement in providing value-relevant information to investors as well as their ability to anticipate changing economic conditions and adjust the firms' business plans accordingly (Trueman 1986). As discussed further below, incentives to influence investors' assessment of managerial ability may induce managers to herd in their voluntary disclosure decisions.

2.2 Theories of herd behavior

Extensive theoretical evidence exist on rational herding or behavioral convergence by individuals and firms in their respective decisions (see Chamley 2004 and Hirshleifer and Teoh 2003 for extensive summaries of the literature). The most basic cause of convergence in behavior is that agents face similar decision choices, have similar information, and face similar payoffs. Consequently, they can randomly make similar decisions. While such random convergence in behavior has been termed herding in the literature, the focus of this study is on convergence due to the dependence of one firm's disclosure decision on the past disclosure decisions of other related firms. As discussed in the following sections, this dependence arises from two main sources—the use of information reflected in past disclosure decisions (informational herding), and managerial concerns for reputation (reputational herding).

2.2.1 Informational herding

Studies of social learning and rational herds show that, in many economic settings, agents base their decisions largely on the observed decisions of others. This is because past decisions reflect the private information of each acting agent. Using the information reflected in past decisions is rational because gathering supplemental private information or directly analyzing alternatives can be costly and/or time-consuming. However, this process can lead to herd behavior, where agents rely wholly or partly on the information reflected in the past decisions of others and consequently make similar decisions (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992; Welch 1992; Chamley and Gale 1994).¹

Following Bikhchandani, Hirshleifer, and Welch (1992), consider the scenario where a group of industry firms make binary disclosure decisions (disclose or not disclose) in a predetermined sequence. All managers have similar value-relevant information, a conditionally independent signal of the net benefits or payoffs of disclosing such information, and can observe the disclosure choices of all preceding firms in the sequence. If the first few managers receive positive payoff signals and choose to disclose, then the act of disclosure publicly reveals their private belief that the potential benefits of disclosure outweigh the costs. This implicit information may then lead the next manager to either update or replace his/her private belief of the value of disclosure, thus causing him/her to also disclose.² As shown

¹ Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992) and Welch (1992) model herding and the onset of informational cascades. Informational cascades is an extreme case of herding and occurs when an agent ignores his/her private information and relies wholly on the information reflected in others' past decisions.

² In real economic settings, the net benefits of disclosure will vary across industry firms. However, the act of disclosure clearly reveals that disclosure carries positive payoffs. While this revealed information is noisy, it is sufficient to induce other managers to join the disclosing herd.

in models of informational herding, the tendency to make similar disclosure decisions increases with the number of managers taking the same action. Therefore, as more managers choose to disclose (not disclose), the more likely it is that the next manager will also disclose (not disclose).

In this study, the value-relevant information in question is of firms' future capital expenditures. While the nature of the information is similar across industry firms, the information is likely to differ along various lines such as content, quality, etc. Given this diversity, the above scenario extends to one with a continuum of disclosure choices rather than one with a binary choice. For example, a manager can choose to disclose high or low quality information of either a decrease or increase in expenditures, or choose not to disclose at all. Even though managers can make a range of disclosure choices, there is still a discrete difference between disclosure and nondisclosure. Since the act of disclosure carry specific fixed costs, the choice between disclosure and nondisclosure reverts to a discrete choice set, even though disclosure has a continuous character (Bikhchandani, Hirshleifer, and Welch 1998; Hirshleifer and Teoh 2003).³ Herd behavior as in the binary case will still arise but the rate of convergence will be slower since the amount of information revealed to other managers is less noisy. For example, if the first few managers all disclose information of a decrease in capital expenditures, then their decisions clearly reveal that disclosure of a decrease is value-maximizing and thus, may only effect the decisions of those managers who hold similar information of a decrease.

Another important extension to the above scenario is that in real economic settings the sequence of disclosure decisions will be endogenous rather than exoge-

³ The discrete difference between disclosure and nondisclosure is similar to the option of positive investment in a project and not investing at all. Chari and Kehoe (2003) provide a model where the choice between zero investment and a continuum of positive investment amounts still results in herd behavior.

nously predetermined, i.e., managers have the choice of deciding not only whether to disclose but also *when* to disclose. As demonstrated by Chamley and Gale (1994), this induces a *wait-and-see game* where managers strategically delay their disclosure decision so as to take advantage of the information revealed by others' choices. Since managers must trade off the opportunity cost of delaying disclosure and the value of the information gained, then those with precise positive signals will tend to disclose first. If the number of early disclosers is large, then this clearly reveals that disclosure is value-maximizing, thus triggering a disclosing herd. On the other hand, if no or only a few managers disclose, then disclosure stops and a nondisclosing herd is formed.

Informational herding and payoff externalities

In the previous section, the decisions of others generate a pure informational externality because they convey private information about the value of each choice. However, in many economic settings, the decisions of others can also generate direct payoff interactions, where an agent's payoff is affected by the actions of other agents.⁴ In such cases, herd behavior arises not only from the influence of conveyed information but also from the actual or expected payoff interactions between agents' actions (Gale 1996; Choi 1997; Khanna 1998). That is, when the payoff from a particular action increases with the number of agents taking the same action, then others will be induced to join the herd.

With respect to voluntary disclosure decisions, the models of Dye and Sridhar (1995) and Jorgensen and Kirschenheiter (2003) parallel settings of informational herding with payoff externalities. In their models, managers follow the disclosure choices of other managers so as to mitigate negative payoff externalities, i.e., down-

⁴ In the literature, payoff externalities are also termed network externalities, strategic complementarities, or strategic substitutabilities.

ward revisions in stock price. Using a multi-period model, Dye and Sridhar (1995) demonstrate how a firm's disclosure choice is influenced by the disclosure decisions of other industry firms and the resulting interactions with investor perceptions of firm value. Assuming positive correlations among managers' receipt of information, Dye and Sridhar (1995) argue that investors can use the disclosures of one firm to infer whether nondisclosing firms have received information. If investors infer that a firm is withholding information, they can conclude that the information is either "bad" or "no" news, and subsequently revise the firm's stock price downwards. This potential fall in stock price will then induce nondisclosing managers to disclose their information subsequently. As in the case with no payoff interactions, the tendency to disclose with the herd increases with the proportion of disclosing firms within the industry. This is because the more firms that disclose within the industry, the better investors can infer whether a nondisclosing firm has received information.

Jorgensen and Kirschenheiter (2003) provide similar conditions of herding in voluntary disclosure decisions. In their model, payoff externalities result from correlations among firms' private information rather than from correlations among the receipt of information. If firms' information is negatively correlated, then the propensity to disclose is positively associated with the past disclosure decisions of other firms. Specifically, favorable disclosures by early movers force nondisclosers to join to herd in order to mitigate investors' perception of bad news and the subsequent reduction in stock price. If firms' information is positively correlated, then favorable disclosures by early movers increases investors' perception of good news, thus resulting in upward stock price movements. This positive payoff interaction reduces the incentives for nondisclosing firms to disclose, hence causing them to free-ride off the disclosures of early movers.

2.2.2 Reputational herding

Reputational or agency-based herding is behavioral convergence due to an agent's attempt to obtain or maintain a good reputation with the principal relative to other similar agents (Scharfstein and Stein 1990; Trueman 1994). While theories of reputational herding arise separately in the literature, the conditions for its occurrence are identical to that of informational herding (Ottaviani and Sørensen 2000). In this case, past disclosure decisions generate reputational externalities as well as informational externalities.

Following from Scharfstein and Stein (1990), managers with a lower aptitude for making decisions may follow the disclosure choices of managers with higher aptitudes so as to influence investors' (the principal) assessment of their ability. If a manager mimics the decisions of high-ability managers, investors may infer that the manager has received a signal correlated with that of high-ability managers, and thus, is of high ability. In contrast, if the manager's decision deviates from those of high-ability managers, then the principal is more likely to infer that the manager is of low ability.

2.3 Evidence of herd behavior

Empirically detecting herd behavior is not an easy task. Empirical data on individual or firm behavior usually depicts the decisions taken and not the underlying incentives. Herding is an *ex ante* phenomenon, and as such there are great challenges in using *ex post* data to infer this behavior. Despite these challenges, there exists substantial empirical evidence of herding in stock trades (e.g., Lakonishok, Shleifer, and Vishny 1992; Grinblatt, Titman, and Wermers 1995; Wermers 1999), analyst forecasts and stock recommendations (e.g., Graham 1999; Hong, Kubik, and Solomon 2000; Welch 2000), and capital investment decisions (e.g., Jain and

Gupta 1987; Mei and Saunders 1997).

Many empirical studies of herding fail to directly examine the sources of the behavior—exceptions include Chevalier and Ellison (1999), Graham (1999), and Hong, Kubik, and Solomon (2000), which examine reputational concerns in herding by mutual fund managers, investment newsletters, and analysts, respectively; Grinblatt, Titman, and Wermers (1995) and Wermers (1999), which provide evidence consistent with informational herding in mutual fund trading; and Welch (2000), which attributes informational externalities to analyst herding. This gap in the literature stems primarily from the difficulty in distinguishing between possible incentives to herd. Nevertheless, this study attempts to distinguish between these two sources of herding in the decision to release capital expenditure forecasts.

2.3.1 Evidence of herding in voluntary disclosure decisions

Currently, there is scant empirical evidence of herding in voluntary disclosure decisions. Studies that provide some evidence of herding include Botosan and Harris (2000), which finds that pressure to conform to or mimic competitors' disclosure practices is a key factor precipitating the decision to increase the frequency of segment disclosures. Also, Pincus and Wasley (1994) report that voluntary accounting changes by firms do not appear to be clustered in time and industry, thus implying the absence of herd behavior in rule-based disclosure decisions. More generally, some aspects of the literature argue that various disclosure fads are actually patterns of herding.⁵ For example, it is now popular for firms to disclose “pro forma” earnings along with net income figures in their earnings releases. Firms argue that “pro forma” earnings provide a clearer picture of firm performance. However, it

⁵ A fad is a rapid form of herding. Fads arise when large groups of individuals or firms simultaneously adopt a new behavior (Bikhchandi, Hirshleifer, and Welch 1998). In such cases, very little information is transferred among individuals, thus causing the behavior to be fragile.

is likely that firms are herding in their adoption of this new disclosure technique, or are exploiting the tendency for investors to herd on information (Hirshleifer and Teoh 2003).

Bainbridge (2000), through a thought experiment, offers some insights on informational and reputational herding in disclosure decisions. He argues that the pervasive practice of nondisclosure by firms is possibly due to herding, and that it may be possible to break such cycles of nondisclosure. If herding is due to reputational concerns, Bainbridge argues that mandatory disclosure rules may be the only means of redirecting the herd since the behavior is likely to be sticky. If herding is due to informational incentives, then wide dissemination of the benefits of disclosure can break the cycle. However, the introduction of this new information can trigger rapid shifts toward disclosure.

2.4 Other related studies

This study also relates to prior research on the value-relevance of capital expenditure disclosures and the intra-industry transfer of private information among investors. McConnell and Muscarella (1985) and Chung, Wright, and Charoenwong (1997) document strong market reaction to announcements of changes in future capital expenditures. Thus, providing strong support for the impact of such information on investors' expectations of firm value and managerial reputation.

Information transfer studies such as Foster (1981) and Han and Wild (1990) show that the stock prices of nondisclosing firms react to announcements made by other same-industry firms. Furthermore, Freeman & Tse (1992) and Ramnath (2002) show that earnings surprises and forecasts of same-industry firms are correlated. These findings suggest that investors use the information of disclosing firms to update their assessments of nondisclosing firms. More importantly, they

indirectly support arguments of informational herding as it can be presumed that similar transfers of private beliefs occur among firms.

Chapter 3

Hypotheses

I expect herding in capital expenditure forecasts to be more apparent for firms within the same industry. Correlations among firm values, private information, and/or the receipt of information are greater when firms' operations are similar. More importantly, the conveyance of private beliefs are expected to be greater among industry peers. Likewise, managers are expected to be more concerned about their reputation relative to managers of other same-industry firms. Given these arguments, the following hypotheses investigate the tendency and the incentives for same-industry firms to herd in their capital expenditure forecast decisions.

As discussed beforehand, herding occurs when the tendency to make one disclosure choice increases with the number of firms making the same choice. Hence, to detect herding, I investigate whether the propensity to release capital expenditure forecasts is positively associated with the proportion of prior disclosing firms within the industry. The first hypothesis (in alternative form) is:

H1: The propensity to release capital expenditure forecasts is positively associated with the proportion of prior disclosing firms within the industry.

Given the continuous character of firms' disclosure choices, I further investigate whether the propensity to release capital expenditure forecasts varies with the

content and quality of prior same-industry forecasts. The results of Jorgensen and Kirschenheiter (2003) suggest that herding will vary with the content of the disclosed information. In their model, herding arises when the disclosed information is favorable (unfavorable) and is negatively (positively) correlated with the information held by nondisclosing managers. Even though, in theory, herd behavior can still arise, there is no empirical evidence to suggest how the tendency to herd differs along a continuum of disclosure choices. Hence, I refrain from making any specific predictions of how the propensity to disclose will vary with the information content of prior same-industry forecasts. The second hypothesis is as follows:

H2: The propensity to release capital expenditure forecasts is associated with the information content of prior same-industry forecasts.

Despite limited empirical evidence of herding with continuous choices, it is reasonable to presume that the tendency to herd will be greater when prior same-industry forecasts are of higher quality, i.e., more precise. This is because the transfer of private beliefs among managers will be greater when the disclosed information is more precise. Hence, I expect the propensity to release capital expenditure forecasts to be positively associated with the precision of prior same-industry forecasts. The third hypothesis is:

H3: The propensity to release capital expenditure forecasts is positively associated with the information content of prior same-industry forecasts.

Although the conditions for informational and reputational herding are similar, it is important to separately investigate whether herding in disclosures is driven by managerial concerns for their reputation. Trueman (1986) shows that high-ability managers are more likely to release forecasts early, regardless of the nature of the news. This is because the sooner the forecast is released, the more favorable investors will assess the manager's ability to make good decisions and to recognize

future changes in the firm's environment. Low-ability managers who are less certain of whether to disclose forecasted information may herd in their disclosure decisions so as to be indistinguishable from high-ability managers. Given these arguments, I examine whether relatively less reputable managers are more likely to herd in their capital expenditure forecast decisions. Consistent with Hypothesis 1, I expect the positive association between a firm's forecast decision and the proportion of prior disclosing firms to be higher for low-reputation managers relative to more reputable managers. This is stated in the fourth hypothesis.

H4: The association between the propensity to release capital expenditure forecasts and the proportion of prior disclosing firms within the industry is higher for less reputable managers relative to more reputable managers.

Given the strategic nature of future capital expenditure information, it is expected that the level of disclosure and thus, incentives to herd will vary with the level of industry rivalry. Some theoretical models suggest that, due to high strategic costs, the level of disclosure will be lower for those firms operating in highly competitive industries (Verrecchia 1983). However, other models predict that firms in highly competitive industries will disclose more so as to deter market entry (Darrough and Stoughton 1990; Feltham and Xie 1992). Similarly, empirical analysis provides mixed evidence of the relationship between competition and the level of disclosure. For example, Harris (1998) and Botosan and Harris (2000) both find that disclosure of segment information decreases with the level of competition, whereas Shin (2002) finds that competition increases disclosure when firms compete on capacities and decreases disclosure when firms compete on price.

While mixed evidence exists on the relationship between disclosure and industry competition, studies of herding suggest that incentives to herd will increase with the level of firm rivalry (e.g., Gilbert and Leiberhan 1987; Kennedy 2002). Man-

agers facing tight competition for capital funds at lower costs may herd in their disclosure decisions so as to take advantage of the information held by presumably better-informed rivals. Likewise, reputational concerns due to higher labor market competition may lead managers to pursue similar disclosure strategies or to conform to industry disclosure norms.¹ Consequently, I test the following hypothesis:

H5: The association between the propensity to release capital expenditure forecasts and the proportion of prior disclosing firms within the industry is higher for firms facing high competition.

¹ Defond and Park (1999) find greater use of relative performance evaluation (RPE) in highly competitive industries which results in higher CEO turnover in these industries.

Chapter 4

Research Methodology

4.1 Duration analysis for multiple events

Duration analysis is concerned with analyzing the time to the occurrence of an event. Duration models are widely used in economics and other social sciences, and are rooted in industrial engineering and the biomedical sciences where they are used to describe durations such as the useful lives of machinery and the survival times of treatment recipients (see Kiefer 1988, for a review of the economic duration literature). In accounting, duration models are increasingly being applied to various issues such as the time to financial distress (Chen and Lee 1993), the time to audit firm dismissal (Barton 2004), and durations of consecutive earnings increases (Ke 2004).

I use duration analysis to examine the probability of releasing a capital expenditure forecast and the extent to which incentives to herd may impact the timing of these releases. Duration analysis greatly enhances the ability to offer insights into herding and the temporal dynamics of voluntary disclosure practices. This is because duration analysis explicitly models the timing and sequencing of disclosure events and thus best captures the sequential process of herd behavior. Moreover, duration models—unlike discrete choice models—take into consideration that a firm's

propensity to disclose information can change at an inconstant rate over time as well as allow for the inclusion of time-varying explanatory variables.

Unlike most duration studies, where the respective event occurs only once per subject (e.g., death), disclosure of future capital spending is repeatable over time. Traditional duration models treat repeated events as independent and thus do not consider that subsequent events are likely to be influenced by previous events. To address the possible correlation between multiple forecasts, I apply a variance-corrected duration model for repeated events. Variance-correction models estimate a standard Cox (1972) proportional hazards model and adjust the variance-covariance matrix to account for unobserved individual- or group-specific effects (Lin and Wei 1989). In most cases, a *sandwich* estimator, similar to White’s (1980), is used to produce robust variance estimates.

Let $t = 1, \dots, T$ denote a sequence of discrete time intervals (e.g., weeks); $T \geq 1$ denote the duration or waiting time to disclosure; and let \mathbf{X} denote a vector of time-varying covariates (explanatory variables). Then, the standard Cox model is as follows:

$$h [t | \mathbf{X}(t)] = h_0(t) \exp [\mathbf{X}(t)\beta] \quad (4.1)$$

where the dependent variable $h [t | \mathbf{X}(t)]$ is the “hazard rate” or probability of disclosure during time t conditional on the history of covariates up to time t , β is a

vector of coefficients, and $h_0(t)$ is an unspecified baseline hazard.¹ The baseline hazard is the common probability of disclosure given that all explanatory variables are equal to 0.² The model uses the duration times for each firm to estimate the effects of the explanatory variables on the probability of disclosure during time t .

Multiple forecasts by a single firm are naturally ordered events; i.e., the release of a revised forecast cannot occur before the release of the initial forecast. Given this ordered process, I use the Prentice, Williams, and Peterson (1981) (hereafter PWP) conditional interevent time model for repeated events.³ The PWP model is:

$$h_k [t | \mathbf{X}(t), k - 1] = h_{0k}(t - t_{k-1}) \exp [\mathbf{X}_k(t)\beta] \quad (4.2)$$

where $h_k [t | \mathbf{X}(t), k - 1]$ is the probability of releasing the k^{th} forecast conditional on the history of covariates and the number of forecasts up to time t ; h_{0k} is the baseline hazard of releasing the k^{th} forecast; and $\mathbf{X}_k(t)$ is a vector of covariates that

¹ In probability terms, the precise definition of the hazard rate is the probability of disclosure within the short time interval $[t, t + \Delta t)$ given nondisclosure and a history of covariates up until time t , i.e.,:

$$h [t|\mathbf{X}(t)] = \lim_{\Delta t \rightarrow 0} \frac{P [t \leq T < t + \Delta t | T \geq t, \mathbf{X}(t)]}{\Delta t}$$

² Note that the model does not include an intercept term. The intercept term is implicit in the baseline hazard.

³ Other variance-corrected repeated-events models include the Andersen and Gill (1982) independent increments model and the Wei, Lin, and Weissfeld (1989) marginal risk-set model. However, the Andersen-Gill model lacks the detail and versatility of event-specific models (Kelly and Lim 2000). The Wei-Lin-Weissfeld model assumes that multiple events occur simultaneously, which is inappropriate for this study since forecast events are sequential. In addition, several recent studies compare the efficiencies of all three models and conclude that the PWP model is preferred for repeated events (Kelly and Lim 2000; Bowman 1996)

vary across time and each forecast event k .

The PWP model modifies the Cox model by allowing the estimation of the hazard function to continue beyond the first event. A firm is not “at risk” of releasing the k^{th} forecast until after it releases the $(k - 1)^{\text{th}}$ forecast. Accordingly, the number of firms at risk (the “risk pool”) at time t for the k^{th} forecast is limited to those firms that have released $k - 1$ forecasts. In the model, the durations for each firm are calculated using interevent times; such as, the time to the first forecast, and the time between the first and second forecast. (Figures 1A and 1B depict the ordered forecast process and the data structure for multiple forecasts.) To estimate the model, the data is stratified by risk pool, and separate baseline hazards are estimated for each forecast event. While the baseline hazard is allowed to vary with the number of preceding forecasts, the model does not assume that variable effects also vary across risk pools.⁴

I expect the baseline hazard for subsequent forecasts to be higher as managers have greater incentives to issue forecast revisions in order to preempt investor response to large surprises in expenditures, or to reduce the threat of litigation based on a “duty to update” or “duty to correct” a preexisting forecast that is “inaccurate, incomplete, or misleading”.⁵ This is consistent with Kasznik and Lev (1995),

⁴ To allow both the baseline hazard and variable effects to vary across risk pools, the PWP model can be estimated separately for each event. This should only be done if there are strong theoretical reasons to justify that both the baseline hazard and variable effects vary across events. While I do not assume that variable effects vary across risk pools, the results from estimating the model by risk pool are presented in Section 6 for illustrative purposes.

⁵ According to Loss and Seligman (2003), the duty to correct arises when a prior disclosure is inaccurate at the time that the statement was made. In contrast, a duty to update concerns a disclosure that was accurate when made but becomes misleading due to subsequent events or circumstances. While a duty to correct has been upheld in securities litigations, it is unclear whether there is an obligation to disclose under the duty to update.

which finds that the likelihood of issuing a preemptive earnings warning increases when a previous forecast exists.

4.1.1 Variable specification and measurement

Based on prior studies of herding, I expect herding in capital expenditure disclosure decisions to occur in a relatively rapid manner. Hence, analyses are conducted using weekly time intervals, i.e., $t = 1, \dots, 52$ for an annual disclosure period. Except where noted, all variables are measured as at the end of week $t - 1$ so as to capture the impact of predisclosure conditions. Variables are measured using weekly data; if weekly data is not available, then quarterly data is used. Appendix 1 summarizes the measurement and specification of the variables outlined below.

Detecting herd behavior

To test H1, I investigate whether a firms' propensity to release a capital expenditure forecast in week t is associated with the proportion of firms within its industry that have released one or more forecasts in prior weeks, i.e., over the intervals $[1, \dots, (t - 1)]$. Consistent with theory, the fraction of prior forecasting firms parameterizes increasing informational and reputational incentives to follow the past disclosure decisions of peer firms. The parameter, $PCTDISC_{it-1}^j$, for firm i in industry j as at the end of week $t - 1$, is measured as:

$$PCTDISC_{it-1}^j = \frac{\sum_{l=1}^{t-1} NDISC_{l \neq i, t}^j}{Nj - 1} \times 100 \quad (4.3)$$

where $NDISC_{l \neq i, t}^j$ is the number of forecasting firms (excluding firm i) in indus-

try j , and N^j is the total number of firms in industry j .⁶ Industry classifications are as defined by Fama and French (1997). The parameter is scaled by 100 since percentage points are easier to interpret in the regression results.

Measuring forecast content and precision

While firms have a rich set of disclosure alternatives, I use discrete finite constructs as measures of the content and quality of other firms forecast. These measures are then summarized across all prior weekly intervals for each industry thus, creating a continuous measure of the aggregate information conveyed among industry firms. An aggregate measure of disclosure choices is well suited for empirical tests of herding since the behavior arises when there is a preponderance of actions towards one choice over the others.

The information content of each forecast ($INFO_{it}^j$) is measured as the expected change in annual expenditures relative to last year's total expenditures. $INFO$ equals “-1” if the expected change is a decrease; “1” if it is an increase; and “0” if either no change is expected, or ambiguous or no information is disclosed. For each industry, a summary measure, $IND_INFO_{it-1}^j$, is created, which represents the information content of all other industry forecasts.

$$IND_INFO_{it-1}^j = \frac{\sum_{l=1}^{t-1} INFO_{l \neq i,t}^j}{N^j - 1} \quad (4.4)$$

Since IND_INFO represents the direction of industry-wide changes in capital expenditures, I estimate separate slope coefficients for positive and negative changes in industry capital expenditures. This is done by decomposing IND_INFO into

⁶ For the remainder of the paper, the subscripts i and t are the firm and week indexes, and the superscript j is the industry index.

two separate variables—*NEG_INFO* which equals *IND_INFO* for negative changes, “0” otherwise; and *POS_INFO* which equals *IND_INFO* for positive changes, “0” otherwise.⁷

Forecast specificity offers insight into the quality or precision of the information disclosed by other firms. Following Bamber and Cheon (1998), an ordinal variable, $SPEC_{it}^j$, is used to measure the specificity of each disclosing firms’ forecast. *SPEC* equals “1” for qualitative forecasts, “2” for open-ended estimates (i.e., minimum or maximum), “3” for range estimates, and “4” for point estimates. A summary measure, $IND_SPEC_{it-1}^j$, is created, which estimates the overall level of forecast specificity:

$$IND_SPEC_{it-1}^j = \sum_{l=1}^{t-1} \frac{SPEC_{l \neq i, t}^j}{NDISC_{l \neq i, t}^j} \quad (4.5)$$

IND_SPEC is ascending in the specificity of prior peer forecasts; thus, a positive coefficient on *IND_SPEC* means that firms are more likely to disclose when prior industry forecasts are relatively precise.

Measuring managerial reputation

I distinguish highly reputable managers from less reputable managers using *Fortune’s* annual *America’s Most Admired Companies* survey. Each year, *Fortune*

⁷ Note that disclosures of decreases (increases) in capital expenditures are not clear disclosures of unfavorable (favorable) news. As evidenced by Chung, Wright, and Charoenwong (1997), the nature of the news is dependent on the growth opportunities of the disclosing firm. Also, a large number of forecasts in one direction may be because most industry firms make similar capital expenditure decisions and thus hold similar expenditure information. However, herding will still arise since each firm is assumed to hold independent private signals of the net benefits of disclosure.

magazine ask executives, directors, and analysts to rate the top ten companies (by revenues) in their own industry on eight criteria—quality of management, quality of products and services, employee talent, innovativeness, social responsibility, use of corporate assets, financial soundness, and long-term investment value. While the *Fortune* ranking is a global measure of firm reputation, it incorporates peer views of managerial talent and managerial performance. Moreover, the ranking includes analyst beliefs of managerial reputation, which, following from prior research, are assumed to reflect the beliefs of investors.

I construct a reputation indicator, *REP*, which equals “1” for firms with highly reputable managers; “0” for those with less reputable managers. Those firms included in the survey in at least one of the 3 years preceding the current annual disclosure period are classified as firms with highly reputable managers.⁸ Firms excluded from the survey in all three years are classified as firms with less reputable managers. H4 is tested by estimating the effects of *REP* and the interaction, $REP \times PCTDISC$.⁹

Measures of industry competition

The Herfindahl Index (*HERF*) and the level of capital intensity (*CAPINT*) are used as proxies for industry competition. The Herfindahl Index is a widely used measure of industry concentration and accounts for the relative size and distribution of firms within an industry. The index for each industry is calculated as the sum of the squares of the market shares of each individual firm:

⁸ Using information from the survey, corporate reputation tends to be stable over time. For example, most of the ten Most Admired companies in each year were included in the last five surveys.

⁹ Alternatively, I proxy managerial reputation using CEO tenure, CEO age, and two measures of disclosure credibility. Similar results are obtained when each of these measures are substituted for the *Fortune* reputation indicator in the model.

$$HERF_{t-1}^j = \sum_{i=1}^N \left[\frac{SALES_{it-1}^j}{IND_SALES_{it-1}^j} \right]^2 \quad (4.6)$$

where *SALES* is quarterly sales, *IND_SALES* is the sum of quarterly sales for all firms in the industry, i.e., $\sum_{i=1}^N SALES_i^j$, and *N* is the number of firms in the industry. The index approaches zero when the industry consists of a large number of firms of equal size as in the case of perfect competition. The index increases as the number of firms decreases and as the difference in size between firms increases. Greater values mean higher concentration, less competition, and more market control held by individual firms.

High barriers to entry decreases competition from existing and potential rivals by limiting and deterring entry into an industry. The level of industry capital intensity is traditionally used as a measure of barriers to entry. However, I choose to use firm-specific capital intensity as a measure of barriers to entry for the following reasons.¹⁰ First, whereas firms have relatively little control over exogenous factors of competition such as product market concentration, firms have great control over the level and nature of their capital investments (Harrigan 1981). Second, prior studies suggest that potential market entrants pay greater attention to the competitive investments of individual firms rather than collective industry investments (Rumelt 1991). Third, intra-industry variations in capital intensity may create differences in firms' decision to herd on the past disclosure decisions of rivals. For example, within an industry, less capital-intensive firms may be less informed about the payoffs of providing capital expenditure forecasts, and thus may gain informational advantages from herding on the disclosure decisions of high capital-intensive

¹⁰ Similar results are obtain when capital intensity is measured at the industry level.

firms.¹¹ Capital intensity on a firm-specific basis, $CAPINT_{it-1}^j$, is measured as the ratio of net property, plant, and equipment (net PPE) to total assets. $CAPINT$ is also expressed in percentage points (i.e., $CAPINT \times 100$) for ease of interpretation. To test H5, I estimate the effects of $CAPINT$ and the interaction term, $CAPINT \times PCTDISC$.

Control variables

Based on prior research, additional incentives to disclose capital expenditure forecasts are controlled for as follows:

Deviation from industry capital expenditures The concern for relative performance can lead managers to release a forecast if current expenditures deviate from the industry average. Managers may issue expenditure forecasts to signal to investors their ability to capitalize on future growth opportunities, or anticipate adverse economic changes relative to their peers. Also, managers may issue forecasts in order to offer explanations for deviations which may be viewed negatively by investors. The standardized deviation from industry capital expenditures, $CAPDEV_{it}^j$, is measured as:

$$CAPDEV_{it}^j = \frac{CAP_{it}^j - AVGCAP_{l \neq i,t}^j}{STDEV_CAP_t^j} \quad (4.7)$$

where CAP is capital expenditures scaled by total assets; $AVGCAP$ is the mean scaled capital expenditures for all other industry firms; and $STDEV_CAP$ is the industry standard deviation of scaled capital expenditures. I allow for different

¹¹ Gilbert and Lieberman (1987) find similar within-industry differences in herding in capital investment decisions. Specifically, firms with larger market shares invest in opposition of their rivals, while firms with smaller shares herd.

slope coefficients on positive and negative deviations from the industry average. NEG_CAPDEV equals $CAPDEV$ for negative deviations, “0” otherwise; and POS_CAPDEV equals $CAPDEV$ for positive deviations, “0” otherwise.

Deviation from industry earnings Similar arguments hold when earnings differ from the industry average. Baginski, Hassell, and Kimbrough (2004) argue that managers often augment voluntary earnings forecasts with explanations for forecasted performance. Earnings are usually linked to internal and/or external factors that help to explain the information. Future capital spending is one such factor. Hence, differences in earnings relative to peers may trigger the disclosure of future capital expenditures. For example, when earnings are relatively poor, managers may disclose adjustments to their capital expenditure plans as a corrective measure or as an explanation for poor performance. The standardized deviation from industry earnings, $EPSDEV_{it}^j$, is:

$$EPSDEV_{it}^j = \frac{EPS_{it}^j - AVGEPS_{l \neq i,t}^j}{STDEV_EPS_t^j} \quad (4.8)$$

where EPS is earnings per share excluding extraordinary items; $AVGEPS$ is mean earnings per share for all other industry firms; and $STDEV_EPS$ is the standard deviation of industry earnings per share. Again, I allow for different slope coefficients on positive and negative deviations. NEG_EPSDEV takes on negative values of $EPSDEV$, “0” otherwise; and POS_EPSDEV takes on positive values of $EPSDEV$, “0” otherwise.

Level of analyst following Pressure from analysts for proprietary information may lead firms to increase disclosure (Lang and Lundholm 1996). Alternatively, firms with low analyst following may increase disclosure in an effort to attract fi-

nancial analysts (Healy, Hutton, and Palepu 1999). The level of analyst following, $FOLLOW_{it-1}^j$, is measured as the number of financial analysts following the firm. This measure is based on the last available analyst forecast information in the First Call database prior to the end of week $t - 1$.

Firm size Firm size controls for the cost of issuing information, which is greater for small firms, and investor demand for information production, which is greater for large firms.¹² Prior research consistently documents a positive association between firm size and voluntary disclosures (e.g., Frankel, McNichols, and Wilson 1995). Firm size ($SIZE_{it-1}^j$) is measured as the natural logarithm of the market value of common equity.

Proprietary disclosure costs Capital expenditure forecasts are likely to carry high proprietary costs, which may deter disclosure. In addition to high capital-intensive firms and firms operating in highly competitive industries, these costs are even higher for high-technology (high-tech) firms and firms with high growth prospects. Following Bamber and Cheon (1998), the ratio of market value to book value of common equity (MB_{it-1}^j) is used to control for proprietary costs.

Analyst forecast dispersion Firms with high information asymmetry increase voluntary disclosures in order to reduce investors' incentives to acquire costly private information (Botosan 1997; Botosan and Plumlee 2002). Dispersion in analyst earnings forecasts is interpreted as a measure of both uncertainty (Swami-

¹² An alternative proxy for the demand for information is analyst following. Large firms typically have larger analyst coverage given the high interest in these companies. Therefore, I expect that firm size will be highly correlated with the level of analyst following. As detailed in the next section, this collinearity is corrected for when the variables *REP*, *FOLLOW*, and *SIZE* are orthogonalized so as to remove biases of firm size and corporate visibility from the reputation indicator variable.

nathan 1991) and lack of consensus (Lang and Lundholm 1996; Barron, Kim, Lim, and Stevens 1998). Therefore, analyst forecast dispersion is seen as a joint measure of uncertainty and information asymmetry. Analyst forecast dispersion ($DISPERSE_{it-1}^j$) is measured as the standard deviation of analysts' forecasts divided by the median forecast. This is based on the last available analyst forecast information in the First Call database prior to the end of week $t - 1$.

Liquidity Prior research documents a negative association between liquidity and voluntary disclosures (e.g., Healy, Hutton, and Palepu 1999). The level of firm liquidity (LIQ_{it-1}^j) is measured as the natural logarithm of the ratio of the volume of shares traded to total shares outstanding.

Issuance of equity and/or debt Prior studies evidence a positive association between disclosure quality, disclosure frequency, and the decision to issue equity and/or debt (e.g., Lang and Lundholm 1993). $ISSUE_{it+2years}^j$ equals "1" if firm i registers a public debt or equity offering in the two years (104 weeks) following week t ; "0" otherwise.

Disclosures around earnings announcements Firms tend to increase their disclosure of valuable information around earnings releases (Kasznik and Lev 1995). $EARNREL_{it}^j$ is coded "1" for each week that annual or quarterly earnings is released; "0" otherwise.

Given the above variables, equation (4.2) is rewritten as follows:¹³

$$h_k [t | \mathbf{X}(t), k - 1] = h_{0k}(t - t_{k-1}) \exp \left[\begin{array}{l} \beta_1 PCTDISC_k + \beta_2 NEG_INFO_k + \\ \beta_3 POS_INFO_k + \beta_4 IND_SPEC_k + \\ \beta_5 REP_k + \beta_6 (REP_k \times PCTDISC_k) + \\ \beta_7 HERF_k + \beta_8 (HERF_k \times PCTDISC_k) + \\ \beta_9 CAPINT_k + \beta_{10} (CAPINT_k \times PCTDISC_k) + \\ \beta_{11} NEG_CAPDEV_k + \beta_{12} POS_CAPDEV_k + \\ \beta_{13} NEG_EPSDEV_k + \beta_{14} POS_EPSDEV_k + \\ \beta_{15} FOLLOW_k + \beta_{16} SIZE_k + \beta_{17} MB_k + \\ \beta_{18} DISPERSE_k + \beta_{19} LIQ_k + \beta_{20} ISSUE_k + \\ \beta_{21} EARNREL_k \end{array} \right] \quad (4.9)$$

4.1.2 Additional specifications and analyses

Orthogonalizing the reputation indicator

Prior studies of the *Fortune* survey find that the ranking is highly positively correlated with firm size and measures of corporate visibility such as press and analyst coverage (Fombrun and Shanley 1990; Brown and Perry 1994). Analyst coverage helps to discipline and motivate managers since corporate decisions are closely monitored and publicized (Chung & Jo 1996). As such, the extent to which managers mismanage corporate assets is likely to be lower for those firms with large analyst following. In addition, analyst coverage directly affects investors' assessment of reputation by directing their attention to such issues as managerial quality

¹³ Firm and time subscripts and the industry superscript are suppressed for readability.

and firm performance. The positive association between the *Fortune* ranking and firm size is largely due to the fact that the survey is conducted using the larger firms within an industry. Also, countless studies find a positive association between the level of analyst following and firm size. Hence, the association between the ranking and firm size may also be interpreted as being due to corporate visibility.

To remove the possible confounding effects of size and analyst following on the reputation indicator, I orthogonalize *REP*, *FOLLOW*, and *SIZE* using the modified Gram-Schmidt procedure (Golub and Van Loan 1996). All estimations of equation 4.9 are then conducted using the orthogonalized values of these variables. The interaction between *REP* and *PCTDISC* is also calculated using the orthogonalized values of *REP*.

Treatment of tied disclosure events

In Cox regressions, the ordering of events in continuous time is relevant. When discrete time intervals are used, multiple firms are recorded as disclosing at the same time (termed “tied” events). As such, the exact ordering of disclosure events is unclear. To correct for this, the Efron (1977) method of handling tied events is used. The Efron method approximates the ordering of events using probability weights. For example, if firms A and B disclose within the same week, the Efron approximation averages the probability of firm A disclosing first and the probability of firm B disclosing first.

Nonparametric duration analysis

Before estimating the PWP model, I nonparametrically estimate and analyze the forecast hazard using the Nelson-Aalen cumulative hazard function,

$$\hat{H}(t) = \sum_{i=1}^T \frac{NDISC_t}{N_t} \quad (4.10)$$

where N is the number of firms at risk during week t , and $NDISC$ is the number of firms that released a forecast in week t . The Nelson-Aalen function is based strictly on the raw data and treats each forecast release as an independent event. Hence, the Nelson-Aalen estimates may over- or underestimate the true hazard. Nevertheless, the estimates provide useful preliminary descriptives of the forecast hazard.

Chapter 5

Data and Sample Selection

Corporate managers often release in the business press an internally generated forecast of annual capital expenditures in advance of the release of actual spending in annual financial reports. I hand-collect forecasts of 2000 and 2001 capital expenditures for all firms across all industries from the following business press sources: *Business Wire*, *PR Newswire*, *The Dow Jones News Service*, and *The Wall Street Journal*.^{1,2} Press releases containing forecasts are identified using the terms, “capital budget,” “capital expenditures,” “capital investments,” “capital spending,” “long term expenditures,” and “planned expenditures.”³ The disclosure of forward-looking information is more likely as next year’s information arrives during the current year. Therefore, I collect forecasts of 2000 expenditures from the fourth quarter of 1999 through to the third quarter of 2000 (4Q 1999 - 3Q 2000) and like-

¹ The collection of press releases ends in 2001 since data for the subsequent two years is needed to determine whether the firm expects to issue equity and/or debt.

² Similar to Miller and Piotroski (2000), the earliest and most comprehensive disclosures are identified mostly through the wire services.

³ The search terms are expanded as some firms describe capital expenditures using different terms. Also, if I discern that a forecast earlier than the one collected exists, then a wide search using the company’s name and ticker symbol is conducted so as to identify the earlier forecast. This is done so as to identify all initial forecasts.

wise for 2001 expenditures (4Q 2000 - 3Q 2001). For each forecast, the release date is recorded and the information content and specificity coded. To be included in the final sample, releases must satisfy the following criteria:

1. They must include information directly pertinent to future capital spending decisions, i.e., quantitative or qualitative information on future capital expenditures, changes in budgeted expenditures, or on planned or incomplete projects.
2. They must be authored by a company source. Releases authored by a non-company source, typically a business reporter, are retained if initiated by a company contact. In most cases, these contain direct quotes from company officials.
3. Press releases that contain the same information as a prior release are eliminated; i.e., only releases that offer new or revised information are retained.
4. If duplicate releases occur on the same date, then either the earliest or most comprehensive release is retained.
5. Only releases pertaining to expenditures at the corporate or divisional level are included. Information of expenditures by subsidiaries or partners of a strategic alliance or joint venture are not considered.
6. All types of releases are retained if they include a capital expenditure forecast; i.e., releases of annual and quarterly earnings, earnings forecasts, cost reductions, etc. are retained if a capital expenditure forecast is embedded.
7. Only firms listed on the NASDAQ, NYSE, or AMEX are included.

The necessary accounting and stock price data are collected from the COMPUSTAT/CRPS merged database. Analyst dispersion and following are estimated

using data from the First Call database. Registrations of public debt and/or equity offerings are determined from the SDC Platinum Global Corporate Financing database.

Using the above criteria, I identify 1775 capital expenditure forecasts by 878 publicly-traded firms over the 8 quarters, 4Q 1999 to 3Q 2001. The forecast dates are grouped into 104 weekly time intervals. Eleven firms issued two or more forecasts within the same week. Duration models prohibit multiple events by the same firm within the same time interval. Therefore, for these 11 firms either the earliest or the most specific forecast is retained. This reduces the number of forecasts to 1763. Of this total, 637 forecasts are of 2000 expenditures while 1126 forecasts are of 2001 expenditures. This sharp increase is possibly due to the implementation of Regulation Fair Disclosure (Reg FD) which took effect on October 23, 2000 or to the economic decline which began in late 2000.⁴ Studies such as Heflin, Subramanyan, and Zhang (2003) document a substantial increase in the volume of firms' voluntary forward-looking disclosures after the implementation of Reg FD. Expected slumps in business performance may have prompted a greater proportion of firms to forecast adjustments to their 2001 expenditure plans.⁵

⁴ In November 2001, the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER) officially reported that the decline in business activity across the U.S. economy began in March 2001 (see Business Cycle Dating Committee, NBER, November 26, 2001). However, a recent article in *The Wall Street Journal* (January 22, 2004) reports that the NBER is considering revising the start date of the recession to as early as November 2000.

⁵ The implementation of Reg FD and the decline of the economy in the 2001 period is not expected to adversely impact the study's results for the following reasons. First, these events affect all firms in the sample. Second, the duration analysis is conducted separately for each time period. Results from estimating the model separately for each disclosure period (see Table 4) confirm these expectations. In addition, the results from the pooled estimation remain unchanged when a Reg FD indicator variable is included for the week of October 23, 2000 and all weeks thereafter.

Given the differences in their disclosure environment, I exclude 56 forecasts by 32 utilities (SIC 49XX) and 32 forecasts by 23 financial and insurance institutions (SIC 6XXX) as well as 357 forecasts by 185 foreign firms. To ensure tractability, I eliminate 319 forecasts by 191 firms with a non-December 31 fiscal year-end. This procedure yields a total count of 1021 forecasts (473 firms). To conduct the duration analysis, I separate the sample into two distinct forecast periods—the 4 quarters, 4Q 1999 to 3Q 2000, which spans the release of 2000 expenditure forecasts, and the 4 quarters, 4Q 2000 to 3Q 2001, which spans the release of 2001 forecasts. For each forecast period, the first week is recorded as $t = 1$. All firms must exist or be at risk at the beginning of week 1; i.e., newly entering firms are not added to the risk pool after week 1. Also, firms must have the relevant data from COMPUSTAT/CRSP and First Call at the beginning of the period. However, firms are not required to have observations for the entire 52-week period.⁶ Based on these restrictions, I eliminate an additional 91 firms. Using the same restrictions, the data panel is completed by adding all other U.S. incorporated publicly-traded firms with a December 31 year-end. These firms are categorized as the set of nondisclosing firms.⁷

Due to the manner in which incentives to herd are operationalized, I include only those industries with at least two forecasting firms and those with four or more firms.⁸ Following Collins, Maydew, and Weiss (1997) and Brown, Lo, and Lys (1999), all firms with negative market-to-book values are excluded. These deletions

⁶ The shortest time-series for any firm in the sample is four weeks. Restricting the sample to firms with complete information for the full 52-week period reduces the sample size and creates a survivorship bias.

⁷ Some firms classified as nondisclosing firms may have issued a capital expenditure forecast which failed to appear in the search results. However, this should not adversely affect the paper's findings.

⁸ I use 4-digit SIC codes to place each firm into one of 48 industry classifications as defined by Fama and French (1997).

result in a final full sample of 139,242 firm/weeks (1981 firms). The 2000 and 2001 sub-samples are 62,675 firm/weeks (1376 firms) and 76,567 firm/weeks (1712 firms), respectively. The forecast count for the full sample is 742 (354 firms). For the 2000 and 2001 sub-samples, the counts are 236 (161 firms) and 506 (292 firms), respectively.⁹

For each forecast period, the sample is separated into three risk pools—firms likely to release the first forecast, the second forecast, and three or more forecasts. I collapse the third and higher forecast event into a single risk pool since few firms release more than two forecasts. To mitigate the effects of outliers, I winsorize the full sample and each sub-sample by setting extreme values of all continuous variables equal to the values at the 0.5% and 99.5% levels. I winsorize these values instead of deleting them in order to conserve the number of observations.¹⁰

5.1 Descriptive evidence

Appendix 2 provides examples of capital expenditure forecasts issued by firms in the transportation and telecommunications industries and their respective information content and specificity coding. Figures 2A and 2B depicts the distribution of the forecast content and specificity, respectively, for the 2000 and 2001 sub-

⁹ The sum of the number of forecasting firms in each period differs from the total number of forecasting firms in the full sample because of newly entering firms, exiting firms, some firms not always issuing a forecast, and failure to identify a forecast from the press sources used. There are 185 new forecasting firms in the 2001 sub-sample, whereas 54 firms that forecasted their 2000 expenditures were either not included in the 2001 sub-sample or failed to forecast their 2001 expenditures. Restricting the sample to all firms that release a forecast in both periods greatly reduces the number of forecast counts and induces a survivorship bias.

¹⁰ Similar results are obtained using both the non-winsorized sample and a sample winsorized at the 1% and 99% levels.

samples. From Figure 2A, 25.4% (60 of 236) of forecasts signal a decrease in capital expenditures for 2000 compared to 42.7% (216 of 506) for 2001. This dramatic increase is more likely due to the 2001 recession. From Figure 2B, sample forecasts are relatively precise since 62.7% (148 of 236) and 66.8% (338 of 506) of 2000 and 2001 forecasts, respectively, provide a point or range estimate. Figure 3 presents the weekly distribution of forecasts. Note that there are distinct spikes in the distribution in the weeks following the end of each quarter. However, this is not striking since these increases coincide with the disclosure periods for annual and quarterly earnings.

Panel A of Table 1 presents the quarterly pattern of capital expenditure forecasts along with the Nelson-Aalen hazard estimates as at the end of each quarter. It is evident that most firms release at least one capital spending forecast within the last quarter of the previous year and the first quarter of the current year. The Nelson-Aalen estimates show that the disclosure rate increases significantly in the first two quarters of each period and then increases at a decreasing rate for the last two quarters. Also, the disclosure rate is significantly higher in the 2001 period with the hazard estimates increasing to 34.55% versus 19.91% in the 2000 period. The functional form of the forecast rate is further depicted in Figures 4A and 4B, which plots the Nelson-Aalen smoothed and cumulative hazard functions, respectively, for each forecast period.¹¹ These plots clearly show that the forecast rate varies over the disclosure period and is increasing at a decreasing rate.

Since the level of disclosure is expected to differ by industry competition and firm capital intensity, I estimate and plot comparative cumulative hazard functions

¹¹ The smoothed hazard function is derived by estimating the hazard contribution for each week, i.e., by taking the steps of the Nelson-Aalen cumulative hazard, $\widehat{H}(t)$. More precisely, the estimated hazard contribution for each weekly interval is $\Delta \widehat{H}(t) = \widehat{H}(t) - \widehat{H}(t - 1)$. The hazard contributions are then kernel smoothed.

for high- and low-competition industries, and for high and low capital-intensity firms. An industry is classified as high (low) competition if its Herfindahl Index is less than (greater than) the mean index of the sample (which is 0.14). Likewise, a firm is classified as high (low) capital-intensity if its capital intensity ratio is greater than (less than) the mean sample ratio (which is 29.72%). Figure 5 presents comparative plots by industry competition (5A) and capital intensity (5B) for the full sample while Figures 6 and 7 present comparative plots for each forecast period. Figure 5 show significantly higher forecast rates for firms operating in less competitive industries and those with high capital-intensity. This suggests that high proprietary costs resulting from either high product market competition or low barriers to entry substantially reduce the propensity to provide forward-looking expenditure information. Figures 6 and 7 show similar differences between both disclosure periods. However, from Figure 6, the forecast rate for high-competition industries increases more so in the 2001 period relative to low-competition industries. From Figure 7, low capital-intensity firms experienced a relatively greater increase in their forecast rate across both periods. These findings may indicate that the implementation of Reg FD and the economic downturn had a greater impact on the disclosure strategies of firms facing relatively high competition.

I also estimate and plot separate cumulative hazard functions for each disclosure event. Figure 8 plots the hazard functions for the first, second, and third or higher forecast event. It is clear that the propensity to release a forecast revision is substantially higher than that of releasing the initial forecast. This provides strong support for the use of the PWP model over other traditional duration models.

Table 2 presents comparative data for sample firms (Panel A) and all firms in the COMPUSTAT/CRSP database with available quarterly data (Panel B).¹² Panels

¹² Here, quarterly data are presented instead of weekly data since sales, earnings, and asset-based information is not available on a weekly basis.

C and D present descriptives for all quarters in which a firm is classified as either a disclosing or nondisclosing firm, respectively. For each forecast period, a firm is classified as a disclosing (nondisclosing) firm if it issues at least one forecast (no forecast). From Panels A and B, sample firms are slightly larger than the average firm with a mean market value of equity of \$3.865B versus \$2.305B and mean sales of \$608.2M versus \$427.6M. Sample firms are more capital intensive, but their earnings performances are comparable to those of the average firm. From Panels C and D, disclosing firms are significantly larger than nondisclosing firms and outperform them.

Table 3 presents descriptive statistics of the forecast durations (Panel A) and continuous independent variables (Panel B) for the full sample and each sub-sample. The statistics for the forecast durations are calculated using only disclosing firms. Statistics for current quarter earnings per share and capital expenditures are also provided. From Panel A, the mean forecast duration for the full sample is 24.21 weeks. As expected, the mean forecast duration is shorter for 2001 forecasts in comparison to 2000 forecasts. From Panel B, 8.97% of other same-industry firms, on average, release at least one forecast. The statistics for the information content and specificity constructs show that on average most peer firms forecast an increase in expenditures and that forecast specificity is relatively high. Average quarterly earnings per share declines dramatically between the two forecast periods. However, there are no significant differences in the standardized deviations from industry earnings across the two periods.

Chapter 6

Main Results

6.1 The PWP conditional hazard model

Table 4 presents the results of the estimation of equation 4.9. The orthogonalized values of *REP*, *FOLLOW*, and *SIZE* are denoted using the subscript *O*, i.e., *REP^O*, *FOLLOW^O*, and *SIZE^O*. The *z*-statistics for all coefficients are based on Lin & Wei's (1989) robust variance estimates. The Efron (1977) approximation is used to handle tied events. Columns 1 to 3 present the pooled results for the full sample, whereas columns 4 and 5 present the results for each sub-sample. For ease of interpretation, I report the percentage change in the forecast hazard given a one-unit change in each independent variable while holding all others constant. Since the independent variables have different scales, I also report the one-standard-deviation percentage change.

The one-unit percentage change in the hazard rate for each variable *r* is calculated as $100\exp(\beta_r) - 1$. For continuous variables, the one-standard-deviation percentage change is calculated as $100\exp(s_r\beta_r) - 1$ where s_r is the sample standard deviation of variable *r*. For indicator variables, the one-standard-deviation change is based on a change from 0 to 1 and, therefore, equals the one-unit change. The one-standard-deviation change for orthogonalized variables also equals the one-unit

change since orthogonalization produces normalized variables with a standard deviation of 1.

The results strongly support H1. Specifically, the disclosure rate of capital expenditure forecasts is positively and significantly associated with the proportion of same-industry firms that released a forecast in the weeks prior to the current week. The coefficient on *PCTDISC* indicates that, all else equal, a 1% increase in the fraction of forecasting same-industry firms increases a firm's forecast propensity by 5.76%.

The regression results also provide support for H2. The estimated coefficient on *NEG_INFO* is not significant for the full sample but is negative and weakly significant for the 2000 sub-sample. This provides weak evidence of an increase in the propensity to disclose when other same-industry forecasts signal a decrease in capital expenditures. The significantly negative coefficient on *POS_INFO* indicates that firms are less likely to disclose when the majority of same-industry firms signal either an increase or no change in capital expenditures. This is consistent with the arguments of Jorgensen and Kirschenheiter (2003) and suggests that firms are likely to free-ride on other firms' disclosures of an expected increase in expenditures relative to disclosures of an expected decrease.

With respect to H3, the estimated coefficient on *SPEC* shows that a firm's forecast propensity increases with the specificity of prior same-industry forecasts. This is consistent with theories of informational herding as the transfer of private information between peer firms will be greater when disclosures are more precise.

Together, the findings from *PCTDISC* and the information constructs confirm that herding in disclosures is partly driven by informational incentives, and that firms do take advantage of the information reflected in the disclosures of other firms. Moreover, while decreases (increases) in future capital expenditures is not a clear cut signal of bad news (good news), the findings do suggest that there is a bad

news/good news effect between the information content of prior disclosures and the tendency to herd.

The negative and significant coefficient on the interaction between REP^O and $PCTDISC$ suggests that herding in forecast decisions is also driven by reputational incentives. Specifically, the coefficient indicates that the tendency to herd is higher for less reputable managers in comparison to more reputable ones. That is, the total effect of $PCTDISC$ on the propensity to disclose decreases by 0.70% for every one-unit increase in REP^O .

The main effect of REP^O is positive and shows that the propensity to disclose is increasing in the level of managerial reputation. However, the results for each sub-sample show that reputation plays a much greater role in the decision to forecast 2001 expenditures. Given the decline in average firm performance during this period, this suggests that high-ability managers are more likely to disclose relevant capital expenditure information when faced with adverse economic changes. This is consistent with Trueman's (1986) argument that high-ability managers have greater incentives to voluntarily release information in order to signal their ability to anticipate economic changes in the firm's environment.

As expected, the coefficients on $HERF$ and $CAPINT$ show that the propensity to disclose capital expenditure forecasts increases with the level of product market concentration and the degree of firm capital intensity. In other words, lower product market competition and higher barriers to entry decrease proprietary disclosure costs which in turn leads to higher levels of disclosure. H5 proposes that the tendency to herd will be higher for firms facing relatively high industry rivalry. The coefficients on the interactions of $HERF$ and $CAPINT$ with $PCTDISC$ corroborate this hypothesis. Specifically, the effect of other firms' past disclosure decisions is greater for firms in low-concentration industries and firms with low capital requirements.

The estimated coefficients on the control variables are consistent with prior research. Specifically, analyst following and firm size increase the forecast propensity, whereas proprietary costs decrease it. The results of the separate regressions for each forecast period provide some evidence that information asymmetry and the issuance of debt or equity positively impacts the forecast propensity. Also, the results show that both positive deviations in capital expenditures and negative deviations in earnings increase the forecast propensity. This indicates that firms increase disclosure when expenditures exceed the industry average and when relative performance is poor. In contrast, the propensity to disclose decreases when capital expenditures exceed the industry average.

6.2 The by-risk pool PWP hazard model

The PWP model does not assume that variable effects differ across risk pools. However, I re-estimate the PWP model separately for each risk pool in order to allow the variable effects to vary by forecast number. Table 5 presents separate results for firms at risk of issuing the first and second forecast and those at risk of issuing three or more forecasts. As in the stratified model, each forecast event is allowed its own baseline hazard; here, each variable's effect on the hazard is also allowed to vary for each subsequent forecast.

The results in column 1 are similar to those from traditional duration models which simply estimate variable effects for the first forecast event. Comparing column 1 of Table 5 with the results in column 1 of Table 4, it is clear that traditional models overestimate variable effects relative to the PWP model. From the results in columns 2 and 3 of Table 5, the effect of the limited risk pools is immediately apparent. Estimates for each subsequent forecast are based on successively smaller numbers of observations, resulting in a uniform decrease in the z-statistics across

the columns. Similarly, the overall significance of the models decreases with the increasing number of forecasts, thus indicating that the model performs progressively worse in explaining the forecast rate as more forecasts occur. Together, these results are consistent with the warnings of prior research which suggest possible efficiency losses of event-specific variable effects (e.g., Wei, Lin, & Weissfeld 1989). Hence, caution must be exercised when interpreting these results.

Nevertheless, the results reveal interesting aspects of the nature and effects of repeated forecast events. The signs of most of the estimated coefficients are stable across the risk pools. For those that fluctuate, in most cases, the coefficients are not precise enough to conclude that the fluctuation is not merely a statistical artifact. The effect of *PCTDISC* is positive for all three risk pools but significant for only the first and third. This indicates that incentives to herd are present for only the initial forecast and the third or higher revisions. The effects of managerial reputation largely disappear after the initial forecast event but their signs are stable across all three risk pools. Interestingly, the interactions between *PCTDISC* and the proxies for firms' competitive environment are strongly significant for all risk pools.

Overall, the results from Table 5, together with the variations in the cumulative hazard for each forecast event as plotted in Figure 8, provide strong evidence that the forecast hazard varies significantly by forecast number. More importantly, the evidence suggests that factors other than those typically used in the voluntary disclosure literature may better explain the propensity to issue forecast revisions. Finally, the results clearly show that the PWP model is superior to traditional duration models when analyzing multiple disclosure events.

6.3 The PWP hazard model with fixed industry effects

As noted beforehand, the convergence among firms' disclosure decisions may be simply because firms have similar information to disclose and have similar private information of the net benefits of disclosure. Since this study is more concerned with convergence due to the interdependence among firms' disclosure decisions, it is necessary to control for unobserved factors which may be independently causing same-industry firms to disclose expenditure forecasts in parallel. This is done by re-estimating the PWP model with fixed within-industry effects. In Cox regressions, fixed industry effects can be included using either industry dummy variables or industry stratifications. Prior research shows that stratified effects are more efficient than dummy variables. This is because industry stratifications allow the baseline hazard and thus the shape of the function to vary across industries. The PWP model with industry stratifications is of the form:

$$h_k^j [t | \mathbf{X}(t), k - 1] = h_{0k}^j (t - t_{k-1}) \exp \left[\mathbf{X}_k^j(t) \beta \right] \quad (6.1)$$

where the baseline hazard function is estimated separately for each industry and each disclosure event. Given this form, equation 4.9 is rewritten as follows:

$$h_k^j [t | \mathbf{X}(t), k - 1] = h_{0k}^j (t - t_{k-1}) \exp \left[\begin{array}{l} \beta_1 PCTDISC_k^j + \beta_2 NEG_INFO_k^j + \\ \beta_3 POS_INFO_k^j + \beta_4 IND_SPEC_k^j + \\ \beta_5 REP_k^j + \beta_6 (REP_k \times PCTDISC_k^j) + \\ \beta_7 HERF_k^j + \beta_8 (HERF_k^j \times PCTDISC_k^j) + \\ \beta_9 CAPINT_k^j + \beta_{10} (CAPINT_k^j \times PCTDISC_k^j) + \\ \beta_{11} NEG_CAPDEV_k^j + \beta_{12} POS_CAPDEV_k^j + \\ \beta_{13} NEG_EPSDEV_k^j + \beta_{14} POS_EPSDEV_k^j + \\ \beta_{15} FOLLOW_k^j + \beta_{16} SIZE_k^j + \beta_{17} MB_k^j + \\ \beta_{18} DISPERSE_k^j + \beta_{19} LIQ_k^j + \beta_{20} ISSUE_k^j + \\ \beta_{21} EARNREL_k^j \end{array} \right] \quad (6.2)$$

Column 1 of Table 6 presents results for the PWP model stratified by industry. Comparative results for the PWP model with industry dummies are presented in column 2. With the exception of the information content constructs, the estimated coefficients from both specifications are largely similar to those presented in Table 4. The estimated coefficients for *NEG_INFO* and *POS_INFO* are no longer significant. However, this is possibly due to the high mathematical correlation among *PCTDISC*, *IND_INFO*, and *IND_SPEC* resulting from the similarity in their measurements. Overall the results from both fixed effects regressions confirm that the previous findings and their interpretations are not driven by random convergence due to unobserved within-industry factors.

Chapter 7

Sensitivity Analyses

To test the robustness of the results, I perform several sensitivity checks. Except where noted, I find that the study's hypotheses continue to be accepted after the following analyses:

7.1 Alternative specification of managerial reputation

I redefine managerial reputation using two separate proxies—the tenure and age of chief executive officers (CEOs). Tenure and age are widely used in prior research to examine managers' career and reputation concerns (e.g., Gibbons and Murphy 1992) and the effect on these concerns on tendencies to herd (e.g., Chevalier and Ellison 1999). For all sample firms, I use the ExecuComp database to identify the appointment and termination dates of each CEO and their age. CEOs with a termination date before or during the first week of 4Q 1999, or missing appointment and termination dates are excluded. CEO tenure is defined as the number of calendar years from the first year of appointment. The data requirement for CEO tenure reduces the sample to 65,087 firm/weeks (794 firms) while for CEO age, the sample reduces to 43,493 firm/weeks (450 firms). When managerial reputation is redefined using CEO tenure, the main effect and the interaction with *PCTDISC* is not sig-

nificantly different from zero. However, when CEO age is used, the main and interaction effects are significant and consistent with arguments of reputational herding. Specifically, the coefficients confirm that younger managers are more likely to herd in their disclosure decisions relative to older managers.

7.2 Historical disclosure policies

Prior research indicates that firms with a history of disclosing forward-looking information are more likely to do so in current periods (e.g., Gibbins, Richardson, and Waterhouse 1990; Miller and Piotroski 2001). This is investigated by including a dummy variable, *PRIORDISC*, which equals “1” for those firms that released a capital expenditure forecast in the prior forecast period; “0” otherwise. Since the disclosure behavior of sample firms prior to the 4Q 1999 is unavailable, this analysis is conducted only for the 2001 period and for those firms that exist in the sample during both periods. Of the remaining 389 forecasts for 2001, 203 are issued by firms which also released a forecast in the previous period. I also interact *PRIORDISC* with *PCTDISC* so as to investigate whether the tendency to herd varies based on prior disclosure history. Consistent with prior evidence, the coefficient on *PRIORDISC* is significant and positive. The coefficient on the interaction term is significantly negative thus indicating that firms with disclosure norms are less likely to herd.

The above finding is consistent with arguments of reputational herding as firms with set disclosure strategies have higher disclosure credibility and thus, may exhibit lower tendencies to herd. However, it must be noted that firms with set disclosure policies can still engage in herd behavior simply by shifting the timing of their disclosures. Since firms which do not shift the timing of their disclosures are probably not herding, I detect and delete 23 firms which issued forecasts in the same

week in both forecast periods. Again, the main results and their interpretations remain unchanged.

7.3 Fixed quarterly effects

Given the distinct differences in the forecast rate over both disclosure periods, I control for seasonal differences in disclosure behavior by including a dummy variable for each fiscal quarter. The magnitude and significance of all variable effects are unchanged from those presented in Table 4. The coefficients on the quarterly dummies indicate significant differences in the forecast rate in only 2Q 2000 and 1Q 2001.

7.4 The implementation of Regulation Fair Disclosure

I also control for the likelihood that the results may be confounded by the impact of Reg FD on firms disclosure strategies. An indicator variable (*REGFD*) which equals “1” for the week of October 23, 2000 and all weeks thereafter (“0” otherwise) is included in the model. The coefficient for *REGFD* is positive and significant, and is consistent with prior studies which show that the implementation of Reg FD resulted in firms increasing the frequency of their voluntary disclosures. However, even after controlling for the effects of Reg FD, the coefficients of the study’s primary variables and their interpretations remain largely unchanged.

7.5 Loss and high-technology firms

Prior research finds that firms are more likely to disclose supplemental information when current earnings are less informative, or when future earnings are more uncertain (e.g., Tasker 1998; Chen, Defond, and Park 2002). Loss firms and high-tech firms have less value-relevant earnings and more uncertain future earnings (Hayn 1995; Francis and Schipper 1999). However, contrasting evidence shows that high-tech firms are less likely to engage in voluntary disclosures due to either high strategic disclosure costs or high litigation costs. To investigate these effects, I include dummy variables indicating those observations with current quarter earnings less than or equal to zero (*LOSS*), and those firms operating in high-tech industries (*HITECH*). Industries classified as high-tech are the semi-conductor (chips), computers, pharmaceutical, electrical equipment, measuring and control equipment, and medical equipment industries. This classification scheme is consistent with Francis, Philbrick, and Schipper (1994) and Kasznik and Lev (1995). Industry classifications are defined by Fama and French (1997).

The estimated coefficients on *LOSS* and *HITECH* are significantly positive and negative, respectively. Thus, indicating that loss firms are more likely to provide capital expenditure forecasts, while high-tech firms are less likely to do so. The findings for high-tech firms are consistent with prior evidence which suggests that high proprietary costs deter disclosure of forward-looking information.

It can also be argued that loss and high-tech firms are less-informed of the potential benefits of disclosure due to either their poor financial information environments or the greater uncertainty of their future performance. As such, these firms may be more likely to herd in their disclosure decisions so as to gain informational advantages from the past decisions of presumably better-informed firms. To investigate these arguments, I interact *PCTDISC* with the *LOSS* and *HITECH*

dummy variables and re-estimate the model. The coefficients on the interaction terms are both positive and significant thus indicating that firms with poor information environments and/or more uncertain future performance are more likely to herd in their disclosure decisions. This finding is consistent with theories of informational herding and provides strong additional support for the argument that herding in disclosures is partly due to informational incentives.

Chapter 8

Concluding Remarks

An area of corporate disclosure behavior that has received little attention is the interaction of voluntary disclosure practices among firms. That is, the influence of one firm's disclosure decisions on the disclosure decisions of other related firms. This study attempts to fill this gap by focusing on the dynamics of herd behavior in the decision to disclose capital expenditure forecasts. Consistent with theories of herding, I find that the propensity to release a forecast is increasing in the fraction of disclosing firms within the industry. Moreover, I find that this association is higher for less capital-intensive firms and firms operating in highly competitive industries. Thus, indicating that relatively high industry rivalry may lead firms to herd in their capital expenditure forecast decisions.

In addition to detecting herd behavior in capital expenditure forecasts, this study provides further evidence of why managers choose to follow the disclosure decisions of related firms. Two possible reasons for the behavior are—managers' use of information reflected in the past disclosure decisions of other firms (informational herding) and managerial incentives to maintain or build a good reputation with investors (reputational herding). The results of the analyses show that the tendency to herd is higher for relatively less reputable managers, and that managers are more likely to disclose expenditure information when prior peer forecasts sig-

nal a decrease in future capital spending and are relatively precise. Overall, these findings indicate that both informational and reputational incentives can lead managers to herd in their disclosure decisions. Therefore, future studies of herding in disclosures should not disregard the possible effects of either of these two factors.

Extensive sensitivity analyses confirm the robustness of the study's findings as well as provide interesting additional findings. Specifically, further analyses show that loss-generating firms and firms operating in high-tech industries are more likely to herd in their disclosure decisions. Consistent with arguments of informational herding, this suggests that poor financial information environments and high uncertainty of future performance may create informational incentives for firms to engage in herd behavior. In addition, consistent with theories of reputational herding, I find that younger managers and firms with set disclosure strategies are less likely to herd in their forecast decisions.

The results of this study has several limitations. First, an important challenge for any empirical study of herding is to rule out random convergence. It is possible that some unobserved factor may be driving firms to disclose in parallel, even when there is no interaction between the disclosure decisions. While controlling for fixed industry effects alleviates concerns of random convergence, it is still likely that omitted firm-specific factors may be creating the appearance of interactive convergence in disclosure decisions. Second, there are potential biases relating to the size of disclosing firms in the sample, which are larger than the average firm. Third, missing data and sample selection biases may eliminate firms which are not herding in their disclosure decisions.

This study contributes to both the voluntary disclosure and herding literature by providing previously undocumented evidence of herding in corporate disclosure practices. Moreover, it attributes herding in disclosures to both informational and reputational incentives. This is in contrast to most empirical studies of herding

which examines only one or none of these incentives. Finally, the study employs a conditional duration model which is more suitable for multiple disclosure events, and which allows the probability of disclosure to vary across time and across forecast events.

The findings of this study highlights numerous extensions for future research. One such extension is whether managers herd in the content of their disclosures. For example, are managers more likely to disclose good (bad) news when other firms disclose good (bad) news? While the results of the study suggest that managers' disclosure choices are conditional on the content of other firms' disclosures, additional analyses are required to provide direct evidence of herding in disclosure content. Another important extension hinges on the expectation that a wait-and-see approach to disclosure will increase information asymmetries between firms and capital market participants. If this is the case, then it remains an open question as to whether herd behavior in voluntary disclosures impacts firms' costs of capital and/or their access to external financing.

Appendix 1

Variable definitions

Herd parameter

PCTDISC the ratio of the number of same-industry firms excluding firm i that have issued a capital expenditure forecast in the weeks $[1, \dots, (t-1)]$ to the total number of industry firms excluding firm i .

Industry competition

HERF the Herfindahl Index for industry j is measured as the sum of the squares of the market shares of each individual firm.

CAPINT the level of current period capital intensity for firm i measured as the ratio of net property, plant, and equipment (long-term assets) to total assets.

Managerial reputation

REP equals “1” if firm i is included in *Fortune's* annual America's Most Admired Companies survey in at least one of the 3 years preceding the current annual disclosure period; “0” otherwise.

Information content and specificity

INFO measure of the information content of the forecast issued by firm i in industry j during week t . Equals “-1” if a decrease in capital expenditures relative to last year's total is forecasted; “1” if a capital expenditure increase is forecasted; and “0” if no change, or ambiguous or no information is reported.

IND_INFO ratio of the sum of INFO for all firms in industry j excluding firm i to the total number of firms in industry j excluding firm i .

NEG_INFO equals IND_INFO if IND_INFO is less than zero; “0” otherwise.

POS_INFO equals IND_INFO if IND_INFO is greater than or equal to zero; “0” otherwise.

SPEC specificity of the capital expenditure forecast issued by firm i in industry j during week t . Equals “1” for qualitative forecasts; “2” for open-ended estimates (minimum or maximum); “3” for range estimates; and “4” for point estimates.

IND_SPEC ratio of the sum of SPEC for all firms in industry j excluding firm i to the total number of disclosing firms in industry j excluding firm i .

Controls

CAPDEV standardized deviation from industry capital expenditures for firm i in week t measured as total capital expenditures for firm i less mean capital expenditures for all firms within the industry excluding firm i scaled by the standard deviation of industry capital expenditures.

NEG_CAPDEV	equals CAPDEV if CAPDEV is less than zero; “0” otherwise.
POS_CAPDEV	equals CAPDEV if CAPDEV is greater than or equal to zero; “0” otherwise.
EPSDEV	standardized deviation from industry earnings for firm <i>i</i> in week <i>t</i> measured as earnings per share for firm <i>i</i> less mean earnings per share for all firms within the industry excluding firm <i>i</i> scaled by the standard deviation of industry earnings per share.
NEG_EPSDEV	equals EPSDEV if EPSDEV is less than zero; “0” otherwise.
POS_EPSDEV	equals EPSDEV if EPSDEV is greater than or equal to zero; “0” otherwise.
FOLLOW	the number of analysts issuing earnings estimates for firm <i>i</i> as at the end of week <i>t</i> -1 . This measure is based on the last available analyst forecast information in the First Call database prior to the end of week <i>t</i> -1.
MB	the level of proprietary disclosure costs as at the end of week <i>t</i> -1 measured as the ratio of market value to book value of common equity.
SIZE	the size of firm <i>i</i> as at the end of week <i>t</i> -1 measured as the natural logarithm of the market value of common equity.
DISPERSE	the dispersion in analyst forecasts for firm <i>i</i> as at the end of week <i>t</i> -1 measured as the standard deviation of analyst forecasts divided by the median forecast. This measure is based on the last available analyst forecast information in the First Call database prior to the end of week <i>t</i> -1.
LIQ	the level of liquidity for firm <i>i</i> at the end of week <i>t</i> -1 measured as the natural logarithm of the ratio of the volume of shares traded in week <i>t</i> -1 to total shares outstanding as at the end of week <i>t</i> -1.
ISSUE	equals “1” if firm <i>i</i> registers a public debt or equity offering in the two years following the week <i>t</i> ; “0” otherwise.
EARNREL	equals “1” for the weeks that firm <i>i</i> reports its annual or quarterly earnings; “0” otherwise.

Appendix 2
Sample capital expenditure forecasts

Capital expenditure forecasts are collected from the following business press sources: *Business Wire*, *PR Newswire*, *The Dow Jones News Service*, and *The Wall Street Journal*. Information content is measured as the expected change in capital expenditures relative to last year's total expenditures - decrease = "-1", increase = "1", and no change or ambiguous information = "0". Information specificity equals "1" for point estimates, "2" for range estimates, "3" for open-ended estimates (minimum or maximum), and "4" for qualitative estimates.

Release Date	Information content (INFO)	Information specificity (SPEC)	Content of CAPEX Disclosure
Transportation			
7/18/2001	Decrease (-1)	Point (4)	UAL Corp.(UAL) will put the brakes on growth plans for its United Airlines unit for the next several years, executives told analysts in a conference call Wednesday. United Airlines president Rono Dutta said the nation's number two carrier will go forward with \$1.4 billion of capital spending this year. However, the company is deferring some aircraft deliveries through 2003, and plans to tail off aircraft capital spending "to zero" by 2004.
7/18/2001	Decrease (-1)	Qualitative (1)	The nosedive in second quarter business passenger bookings hit AMR Corp.(AMR), parent of American Airlines and TWA Airlines, hard on the bottom line, Chief Financial Officer Tom Horton, told analysts in a conference call Wednesday.AMR will continue to look for ways to cut costs. The company has cut \$1 billion of capital spending for the next two years, and, through attrition, will cut down the size of its corporate staff.
7/19/2001	Increase (1)	Point (4)	Despite across-the-board cost-cutting, including some layoffs, that will reduce second-half expenses by \$135 million, Northwest Airlines Corp. (NWAC) has no plans to delay or cut orders for new aircraft, executives said in a conference call with analysts Thursday....Mickey Foret, chief financial officer, said the nation's fourth-largest air carrier has financing in place, through its own resources and with vendors, to take delivery on new planes as planned. Capital spending, including aircraft, is projected to be \$1 billion in 2001, \$1.8 billion in 2002 and \$1.9 billion in 2003.

Appendix 2 cont'd

Release Date	Information content (INFO)	Information specificity (SPEC)	Content of CAPEX Disclosure
Telecommunications			
10/19/2000	No change (0)	Range (3)	Focal Communications Corp.'s (FCOM) capital expenditures for 2001 will probably equal the \$305 million to \$307 million the company estimates it will spend in 2000, Chief Operating Officer John Barnicle said. Speaking at a Kaufman Brothers LP investor conference here Thursday, Barnicle said Focal should see "consistent capital spending" over the next 18 months.
10/23/2000	No change (0)	Point (4)	Gutierrez and SBC Chief Financial Officer Donald Kiernan spoke on a conference call following the release of the company's third-quarter results. SBC exceeded Wall Street's projections, with the exception of its DSL rollout, which came in below analysts' expectations. SBC is on plan for capital spending of \$13 billion in 2000, said Guitierrez. Kiernan said capital spending will be flat next year, with an estimated \$1 billion spent on Cingular, its wireless joint venture with BellSouth Corp. (BLS) and the remaining \$12 billion spent on wireline.
10/30/2000	Increase (1)	Qualitative (1)	Verizon Communications (VZ) Vice Chairman and Chief Financial Officer Frederic Salerno said Monday that the integration of Bell Atlantic Corp. and GTE Corp., which merged in June to form Verizon, continues to proceed smoothly. Verizon's capital spending, estimated at \$18 billion for the year, may see a slight increase in 2001, he said.
11/2/2000	Increase (1)	Point (4)	Time Warner Telecom Inc. (TWTC) Chief Financial Officer David Rayner estimated the company's capital expenditures for 2001 at \$600 million. The estimate is \$200 million above previous projections, reflecting the company's acquisition of GST Telecommunications Inc. (GSTXQ), he said at the Bear Stearns Global Communications conference here. Next year's capital spending, which will be used primarily for fiber construction, is up from an estimated \$350 million for this year, he said.

Table 1
Descriptive analysis of the number of capital expenditure forecasts for the period 4Q 1999 to 3Q 2001

Table 1 presents the quarterly pattern of capital expenditure forecasts for all sample firms along with the Nelson-Aalen cumulative hazard estimate as at the end of each quarter. The number of forecasts are analysed separately for each forecast period. The 2000 forecast period includes the four quarters, 4Q 1999 to 3Q 2000. The 2001 forecast period includes the four quarters, 4Q 2000 to 3Q 2001. The Nelson-Aalen cumulative hazard estimate as at the end of each quarter is the cumulative sum of the ratio of forecasting firms to the total firms at risk during each weekly time interval.

	<u>Total</u>	<u>2000 forecast period</u>				<u>Total</u>	<u>2001 forecast period</u>			
		<u>1999</u>	<u>2000</u>			<u>2000</u>	<u>2001</u>			
		<u>4Q</u>	<u>1Q</u>	<u>2Q</u>	<u>3Q</u>	<u>4Q</u>	<u>1Q</u>	<u>2Q</u>	<u>3Q</u>	
Number of forecasts	236	40	90	58	48	506	124	172	126	84
Number of forecasting firms	161	40	86	55	47	292	108	160	117	77
Number of firms initiating a forecast	161	40	72	29	20	292	108	111	51	22
Cumulative number of forecasting firms		40	112	141	161		108	219	270	292
Number of firms at risk as at quarter end	1376	1355	1156	1147	1140	1712	1669	1405	1384	1366
Nelson-Aalen Cumulative Hazard as at quarter end		2.94%	10.69%	15.72%	19.91%		7.28%	19.45%	28.46%	34.55%

Table 2
Descriptive statistics for the period 4Q 1999 to 3Q 2001

Comparative quarterly data are presented for the full sample and all firms in the CRSP/COMPUSTAT database. Quarterly data are presented since sales, earnings, and asset data are not available on a weekly basis. Panel A presents statistics for all firm/quarters (1981 firms) in the final full sample. Panel B presents the descriptive statistics for all firms with available quarterly data in the COMPUSTAT/CRSP database for the eight quarters, 4Q 1999 to 3Q 2001. Panel C presents statistics for all quarters in which the firm is classified as a disclosing firm. Panel D presents statistics for all quarters in which the firm is classified as a nondisclosing firm. For each forecast period, a firm is classified as a disclosing (nondisclosing) firm if it issues one or more forecasts (no forecast). The sum of the number of firms in Panels C and D differs from the total sample firms as 239 firms are classified as a nondisclosing firm in one forecast period but as a disclosing firm in the other. Market value of equity is equal to beginning of quarter share price times total shares outstanding. The natural log of market value of equity corrects for skewness in the distribution. Earnings per share is quarterly earnings before extraordinary items. Net PPE is net property plant and equipment. With the exception of earnings per share and the natural log of market value of equity, all variables are presented in \$ millions.

	<u>Mean</u>	<u>Std Dev</u>	<u>25%</u>	<u>50%</u>	<u>75%</u>
Panel A: All firm/quarters in final sample (1981 firms)					
Market Value of Equity	3,860.79	17,764.38	115.38	421.39	1559.4
ln(Market Value of Equity)	6.15	1.90	4.75	6.04	7.35
Sales	608.20	2,529.73	25.55	89.77	341.62
Earnings per share	0.06	1.17	-0.12	0.13	0.38
Net PPE	1,001.02	4,268.45	17.39	84.48	460.76
Total Assets	2,924.70	12,931.51	127.16	413.86	1553.3
Panel B: All firm/quarters with COMPUSTAT/CRSP data (7721 firms)					
Market Value of Equity	2,305.92	14,788.84	35.93	146.39	691.69
ln(Market Value of Equity)	5.14	2.12	3.58	4.99	6.54
Sales	427.62	2,138.21	8.38	34.71	164.25
Earnings per share	0.08	10.74	-0.13	0.08	0.33
Net PPE	630.06	3,175.43	5.14	24.50	165.97
Total Assets	3,385.48	23,190.85	57.85	226.91	980.95

Table 2 cont'd

	<u>Mean</u>	<u>Std Dev</u>	<u>25%</u>	<u>50%</u>	<u>75%</u>
Panel C: Disclosing firm/quarters in final sample (354 firms)					
Market Value of Equity	10,700.03	34,447.75	327.81	1,113.85	4901.75
ln(Market Value of Equity)	7.16	2.05	5.79	7.02	8.5
Sales	1,782.98	5,527.29	77.03	287.29	1092.4
Earnings per share	0.20	1.54	-0.03	0.27	0.59
Net PPE	3,466.49	9,397.43	191.40	684.75	2557.1
Total Assets	9,275.74	28,954.87	522.74	1,629.30	5817.3
Panel D: Nondisclosing firm/quarters in final sample (1805 firms)					
Market Value of Equity	2,507.12	11,497.23	102.02	345.49	1248.71
ln(Market Value of Equity)	5.95	1.81	4.63	5.84	7.13
Sales	375.68	1,137.95	21.65	72.52	250.96
Earnings per share	0.04	1.08	-0.13	0.11	0.34
Net PPE	513.04	1,706.91	13.13	55.99	274.87
Total Assets	1,667.66	4,989.78	109.34	327.78	1068.12

Table 3
Descriptive statistics for PWP model variables for the period 4Q 1999 to 3Q 2001

Descriptive statistics are presented for the full sample and separately for each forecast period. The 2000 forecast period includes the four quarters, 4Q 1999 to 3Q 2000. The 2001 forecast period includes the four quarters, 4Q 2000 to 3Q 2001. Panel A reports descriptive data for the weeks to disclosure (duration times). The time to disclosure is calculated using interevent time. Panel B presents descriptive data for all continuous independent variables as well as quarterly earnings per share (EPS) and quarterly capital expenditures in \$ millions (CAPEX). All other variables are as defined in Appendix 1. All variables for the full sample and each sub-sample are winsorized at the 0.5% and 99.5% levels.

	Full sample			2000 forecast period			2001 forecast period		
	Mean	Std Dev	50%	Mean	Std Dev	50%	Mean	Std Dev	50%
Panel A									
Weeks to Disclosure	24.21	12.96	23.00	25.14	13.08	22.00	23.77	12.90	24.00
Panel B									
Continuous Variables									
PCTDISC	8.97	13.01	4.76	6.82	11.36	2.67	10.72	13.97	5.82
HERF	0.14	0.08	0.12	0.14	0.09	0.11	0.14	0.07	0.12
CAPINT	29.72	24.88	21.13	31.70	25.69	23.18	28.11	24.07	19.91
IND_INFO	0.03	0.11	0.00	0.03	0.07	0.00	0.02	0.13	0.00
IND_SPEC	2.52	1.71	2.50	1.97	1.57	1.33	2.97	1.69	3.00
CAPDEV	-0.01	0.94	0.22	-0.01	0.94	0.22	-0.01	0.93	-0.21
EPSDEV	0.00	0.92	0.09	0.00	0.94	0.04	0.01	0.90	0.12
FOLLOW	6.04	5.62	4.00	5.91	5.44	4.00	6.13	5.76	4.00
SIZE	6.13	1.90	6.02	6.18	1.88	6.10	6.09	1.92	5.94
MB	3.86	5.89	2.09	4.23	6.73	2.14	3.55	5.09	2.06
DISPERSE	0.03	0.38	0.01	0.03	0.33	0.01	0.03	0.42	0.01
LIQ	-3.89	1.16	3.86	-3.86	1.14	3.85	-3.92	1.18	-3.87
EPS	0.06	1.17	0.13	0.18	0.64	0.18	-0.03	1.45	0.09
CAPEX	132.21	785.11	11.41	129.66	769.40	12.59	134.29	797.73	10.64

TABLE 4
PWP conditional interevent hazard model for multiple capital expenditure forecasts

Columns 1 present results from the estimation of the PWP model for the full sample. The superscript O indicates orthogonalization. The variables REP, FOLLOW, and SIZE are orthogonalized so as to remove biases of firm size and corporate visibility from the reputation indicator. Columns 2 and 3 presents the one-unit and one-standard-deviation percentage change in the hazard rate for each variable, respectively. The one-unit percentage change for each variable r is calculated as $100[\exp(\beta_r)-1]$. For continuous variables, the one-standard-deviation change is calculated as $100[\exp(s_r\beta_r)-1]$, where s_r is the sample standard deviation of variable r. For indicator variables, the one-standard-deviation change is based on a change from 0 to 1 and therefore, equals the one-unit change. The one-standard-deviation change for orthogonalized variables is also equal to the one-unit change since orthogonalization produces normalized variables with a standard deviation of 1. Columns 4 and 5 present results from the estimation of the PWP model for the 2000 and 2001 forecast periods, respectively. The 2000 period includes the four quarters, 4Q 1999 to 3Q 2000. The 2001 forecast period includes the four quarters, 4Q 2000 to 3Q 2001. All models are estimated in interevent time. Variable definitions are in Appendix 1. All continuous variables for the full sample and each sub-sample are winsorized at the 0.5% and 99.5% levels. Robust z-statistics are in brackets. The z-statistics are computed using Lin and Wei's (1989) robust variance estimates. The Efron (1977) method is used to handle tied disclosure events. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The Wald χ^2 statistic for all models are significant at the 1% level. The PWP model is:

$$h_k[t | \mathbf{X}(t), k - 1] = h_{0k}(t - t_{k-1}) \exp \left[\begin{array}{l} \beta_1 PCTDISC_k + \beta_2 NEG_INFO_k + \\ \beta_3 POS_INFO_k + \beta_4 IND_SPEC_k + \\ \beta_5 REP_k^O + \beta_6 (REP_k^O \times PCTDISC_k) + \\ \beta_7 HERF_k + \beta_8 (HERF_k \times PCTDISC_k) + \\ \beta_9 CAPINT_k + \beta_{10} (CAPINT_k \times PCTDISC_k) + \\ \beta_{11} NEG_CAPDEV_k + \beta_{12} POS_CAPDEV_k + \\ \beta_{13} NEG_EPSDEV_k + \beta_{14} POS_EPSDEV_k + \\ \beta_{15} FOLLOW_k^O + \beta_{16} SIZE_k^O + \beta_{17} MB_k + \\ \beta_{18} DISPERSE_k + \beta_{19} LIQ_k + \beta_{20} ISSUE_k + \\ \beta_{21} EARNREL_k \end{array} \right]$$

Variable	Full sample			By forecast period	
	Coefficient	Unit Δ in Hazard (%)	Std Dev Δ in Hazard (%)	2000 Coefficient	2001 Coefficient
	(1)	(2)	(3)	(4)	(5)
PCTDISC	0.0560 [6.56]***	5.76	107.16	0.0685 [3.13]***	0.0373 [3.36]***
NEG_INFO	1.0304 [0.81]	180.22	3.34	10.8584 [1.89]*	1.1428 [0.84]
POS_INFO	-1.2175 [2.46]**	-70.40	-11.48	-3.9671 [2.41]**	-1.9751 [2.75]***
IND_SPEC	0.1625 [4.67]***	17.64	32.02	0.1048 [1.29]	0.1397 [3.22]***
REP ^O	0.3108 [6.00]***	36.45	36.45	0.1804 [2.01]**	0.3944 [6.50]***
REP ^O x PCTDISC	-0.0070 [3.82]***	-0.70	-10.67	-0.0020 [0.61]	-0.0092 [3.90]***

TABLE 4 cont'd

Variable	Full sample			By forecast period	
	Coefficient	Unit Δ in Hazard (%)	Std Dev Δ in Hazard (%)	2000 Coefficient	2001 Coefficient
	(1)	(2)	(3)	(4)	(5)
HERF	2.5808 [5.13]***	1220.77	23.24	3.0952 [3.84]***	0.9219 [1.24]
HERF x PCTDISC	-0.1166 [4.07]***	-11.01	-30.28	-0.1027 [1.65]*	-0.001 [0.02]
CAPINT	0.0221 [10.41]***	2.23	73.28	0.0271 [7.83]***	0.0230 [9.35]***
CAPINT x PCTDISC	-0.0003 [3.26]***	-0.03	-24.60	-0.0003 [1.45]	-0.0003 [3.08]***
NEG_CAPDEV	0.0732 [1.65]*	7.59	4.47	0.0980 [1.34]	0.0638 [1.27]
POS_CAPDEV	0.1033 [2.29]**	10.88	7.65	0.2115 [3.11]***	0.0497 [1.15]
NEG_EPSDEV	-0.2364 [3.86]***	-21.05	-13.80	-0.2321 [2.29]**	-0.2446 [3.59]***
POS_EPSDEV	0.0401 [0.56]	4.09	2.06	-0.0258 [0.21]	0.0765 [0.90]
FOLLOW ^o	0.2458 [5.33]***	27.86	27.86	0.1527 [2.13]**	0.3051 [6.28]***
SIZE ^o	0.1984 [3.71]***	21.95	21.95	0.3000 [3.38]***	0.1727 [2.99]***
MB	-0.0206 [1.74]*	-2.04	-11.43	-0.0005 [0.04]	-0.0403 [2.33]**
DISPERSE	0.1052 [1.12]	11.09	4.12	0.3971 [2.94]***	0.0406 [0.35]
LIQ	0.0160 [0.32]	1.61	1.88	0.0294 [0.36]	-0.0074 [0.14]
ISSUE	0.0931 [1.04]	9.76	9.76	-0.1392 [0.90]	0.1749 [1.86]*
EARNREL	2.5935 [23.51]***	1237.65	1237.65	2.2945 [12.04]***	2.7721 [21.91]***
Number of Observations	139242			62675	76567
Number of Firms	1981			1376	1712
Number of Forecasts	742			236	506

TABLE 5
By-Risk Pool PWP conditional hazard model

Columns 1 to 3 present results for the first forecast event, the second forecast event, and three or more forecasts, respectively. The superscript O indicates orthogonalization. The variables REP, FOLLOW, and SIZE are orthogonalized so as to remove biases of firm size and corporate visibility from the reputation indicator. Results are presented only for the full sample. All models are estimated in interevent time. Variable definitions are in Appendix 1. All continuous variables are winsorized at the 0.5% and 99.5% levels. Robust z-statistics are in brackets. The z-statistics are computed using Lin and Wei's (1989) robust variance estimates. The Efron (1977) method is used to handle tied disclosure events. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The Wald χ^2 statistic for all models are significant at the 1% level. The PWP model is:

$$h_k[t | \mathbf{X}(t), k - 1] =$$

$$h_{0k}(t - t_{k-1}) \exp \left[\begin{array}{l} \beta_1 PCTDISC_k + \beta_2 NEG_INFO_k + \\ \beta_3 POS_INFO_k + \beta_4 IND_SPEC_k + \\ \beta_5 REP_k^O + \beta_6 (REP_k^O \times PCTDISC_k) + \\ \beta_7 HERF_k + \beta_8 (HERF_k \times PCTDISC_k) + \\ \beta_9 CAPINT_k + \beta_{10} (CAPINT_k \times PCTDISC_k) + \\ \beta_{11} NEG_CAPDEV_k + \beta_{12} POS_CAPDEV_k + \\ \beta_{13} NEG_EPSDEV_k + \beta_{14} POS_EPSDEV_k + \\ \beta_{15} FOLLOW_k^O + \beta_{16} SIZE_k^O + \beta_{17} MB_k + \\ \beta_{18} DISPERSE_k + \beta_{19} LIQ_k + \beta_{20} ISSUE_k + \\ \beta_{21} EARNREL_k \end{array} \right]$$

Variable	Coefficient		
	1st forecast (1)	2nd forecast (2)	>3 forecasts (3)
PCTDISC	0.0632 [5.09]***	0.0085 [0.42]	0.0607 [2.51]**
NEG_INFO	1.4964 [0.69]	0.4869 [0.20]	2.1907 [0.79]
POS_INFO	-1.3670 [1.80]*	-0.2501 [0.26]	1.1314 [0.73]
IND_SPEC	0.1691 [3.91]***	0.1248 [1.77]*	-0.0540 [0.49]
REP ^O	0.3161 [4.76]***	0.0115 [0.11]	0.2027 [1.22]
REP ^O x PCTDISC	-0.0048 [1.64]	-0.0028 [0.79]	-0.0004 [0.08]
HERF	3.1944 [5.76]***	0.9959 [0.73]	0.1136 [0.07]
HERF x PCTDISC	-0.1029 [3.11]***	-0.1785 [1.89]*	-0.2832 [2.50]**

TABLE 5 cont'd

Variable	Coefficient		
	1st forecast (1)	2nd forecast (2)	>3 forecasts (3)
CAPINT	0.0239 [9.68]***	-0.0020 [0.39]	0.0100 [0.94]
CAPINT x PCTDISC	-0.0003 [1.92]*	0.0004 [2.11]**	-0.0001 [0.26]
NEG_CAPDEV	0.0997 [1.51]	0.1334 [1.56]	-0.0450 [0.36]
POS_CAPDEV	0.1172 [2.11]**	0.1698 [2.54]**	0.0484 [0.38]
NEG_EPSDEV	-0.2543 [3.40]***	-0.1095 [1.16]	-0.3413 [2.38]**
POS_EPSDEV	0.1615 [1.67]*	0.0146 [0.11]	-0.2323 [0.96]
FOLLOW ⁰	0.2452 [4.19]***	0.1117 [1.36]	0.2749 [2.00]**
SIZE ⁰	0.2482 [3.90]***	-0.0015 [0.02]	0.2273 [1.59]
MB	-0.0156 [1.08]	-0.0416 [2.14]**	-0.0351 [0.82]
DISPERSE	0.1759 [1.87]*	-0.0193 [0.12]	0.3351 [1.10]
LIQ	0.0175 [0.32]	-0.0544 [0.61]	0.1013 [0.67]
ISSUE	0.2333 [2.11]**	-0.0003 [0.00]	-0.2787 [1.11]
EARNREL	2.4128 [18.95]***	2.8639 [14.32]***	3.0342 [8.53]***
Number of Observations	125178	9719	4345
Number of Firms	1981	354	150
Number of Forecasts	453	185	104

TABLE 6
PWP conditional hazard model with fixed industry effects

Column 1 presents results for the PWP model stratified by industry. Column 2 presents results for the PWP model with industry dummy variables. The superscript O indicates orthogonalization. The variables REP, FOLLOW, and SIZE are orthogonalized so as to remove biases of firm size and corporate visibility from the reputation indicator. Results are presented only for the full sample. All models are estimated in interevent time. Variable definitions are in Appendix 1. All continuous variables are winsorized at the 0.5% and 99.5% levels. Robust z-statistics are in brackets. The z-statistics are computed using Lin and Wei's (1989) robust variance estimates. The Efron (1977) method is used to handle tied disclosure events. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The Wald χ^2 statistic for all models are significant at the 1% level. The PWP model stratified by industry is:

$$h_k^j[t \mid \mathbf{X}(t), k-1] = h_{0k}^j(t - t_{k-1}) \exp \left[\begin{array}{l} \beta_1 PCTDISC_k^j + \beta_2 NEG_INFO_k^j + \\ \beta_3 POS_INFO_k^j + \beta_4 IND_SPEC_k^j + \\ \beta_5 REP_k^j + \beta_6 (REP_k \times PCTDISC_k^j) + \\ \beta_7 HERF_k^j + \beta_8 (HERF_k^j \times PCTDISC_k^j) + \\ \beta_9 CAPINT_k^j + \beta_{10} (CAPINT_k^j \times PCTDISC_k^j) + \\ \beta_{11} NEG_CAPDEV_k^j + \beta_{12} POS_CAPDEV_k^j + \\ \beta_{13} NEG_EPSDEV_k^j + \beta_{14} POS_EPSDEV_k^j + \\ \beta_{15} FOLLOW_k^j + \beta_{16} SIZE_k^j + \beta_{17} MB_k^j + \\ \beta_{18} DISPERSE_k^j + \beta_{19} LIQ_k^j + \beta_{20} ISSUE_k^j + \\ \beta_{21} EARNREL_k^j \end{array} \right]$$

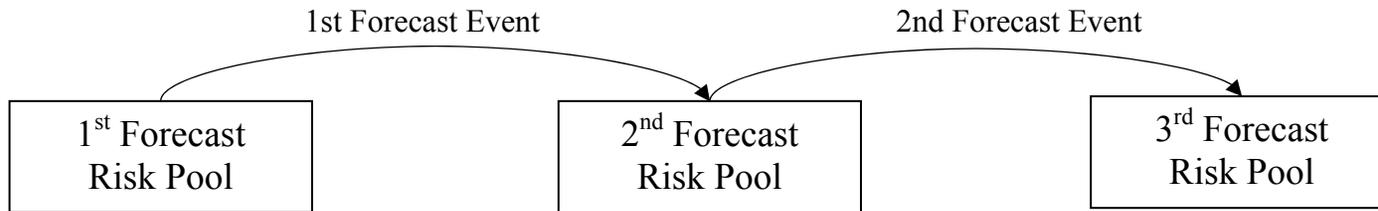
Variable	Coefficient	
	Model stratified by industry	Model with industry dummies
	(1)	(2)
PCTDISC	0.0451 [2.86]***	0.0307 [3.14]***
NEG_INFO	-0.5955 [0.35]	-1.3067 [0.92]
POS_INFO	-0.0678 [0.10]	-0.4801 [0.94]
IND_SPEC	0.1667 [2.91]***	0.1052 [2.63]***
REP ^O	0.2967 [4.95]***	0.2971 [5.34]***
REP ^O x PCTDISC	-0.0071 [2.90]***	-0.0064 [3.49]***
HERF	2.2908 [1.65]*	2.2531 [2.14]**
HERF x PCTDISC	-0.1744 [2.36]**	-0.1253 [3.43]***

TABLE 6 cont'd

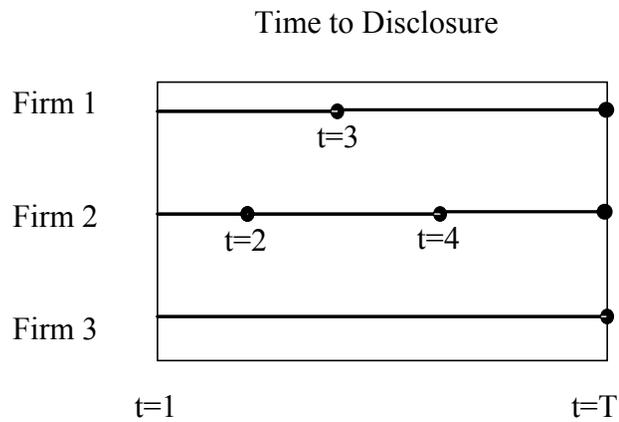
Variable	Coefficient	
	Model stratified by industry (1)	Model with industry dummies (2)
CAPINT	0.0195 [6.06]***	0.0215 [6.81]***
CAPINT x PCTDISC	-0.0001 [0.37]	-0.0002 [2.45]**
NEG_CAPDEV	0.129 [3.05]***	0.0854 [2.00]**
POS_CAPDEV	0.139 [2.87]***	0.1348 [3.04]***
NEG_EPSDEV	-0.1694 [2.35]**	-0.2173 [3.23]***
POS_EPSDEV	0.0705 [0.94]	0.0401 [0.56]
FOLLOW ^o	0.1245 [2.37]**	0.1693 [3.49]***
SIZE ^o	0.1537 [2.78]***	0.1779 [3.04]***
MB	-0.0119 [1.04]	-0.02 [1.69]*
DISPERSE	0.12 [1.15]	0.1005 [1.06]
LIQ	0.0189 [0.36]	0.0365 [0.71]
ISSUE	0.1333 [1.44]	0.1099 [1.23]
EARNREL	2.579 [23.22]***	2.5911 [23.48]***
Number of Observations	139242	139242
Number of Firms	1981	1981
Number of Forecasts	742	742

Figure 1

A: Duration model for multiple capital expenditure forecasts



B: The measurement of duration times



Sample duration data panel

Firm	Week	Disclose	Duration	Risk Pool (k)
1	1	0	1	1
1	2	0	2	1
1	3	1	3	2
1	T	0	T-3	2
2	1	0	1	1
2	2	1	2	2
2	3	0	1	2
2	4	1	2	3
2	T	0	T-4	3
3	1	0	T	1

Figure 2

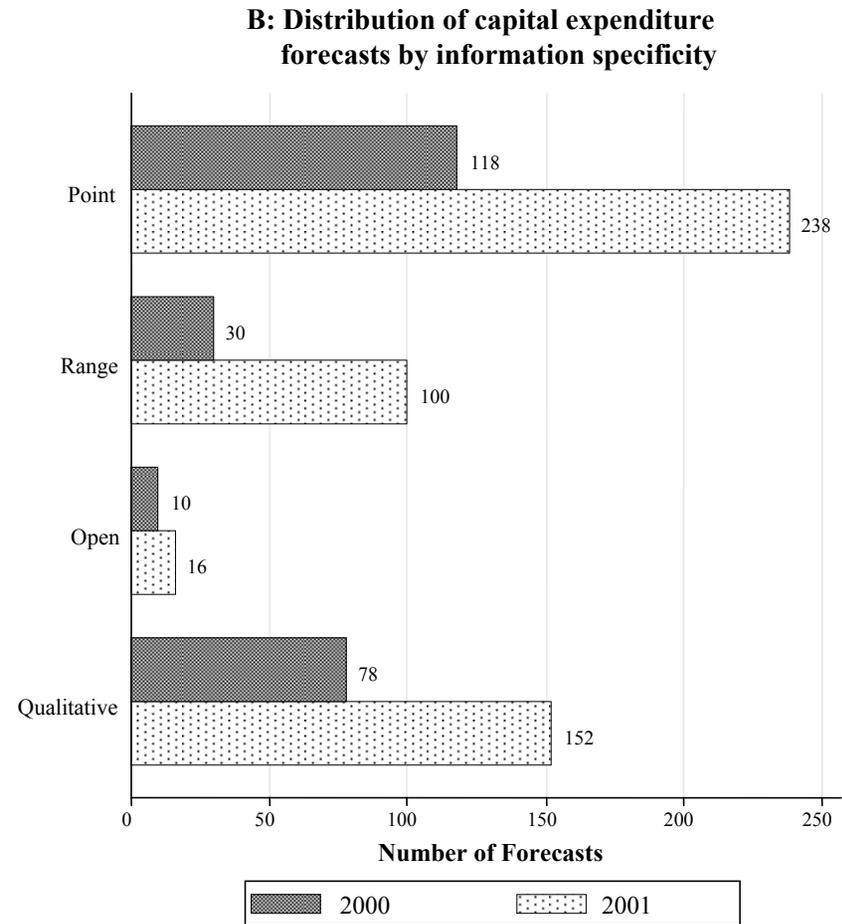
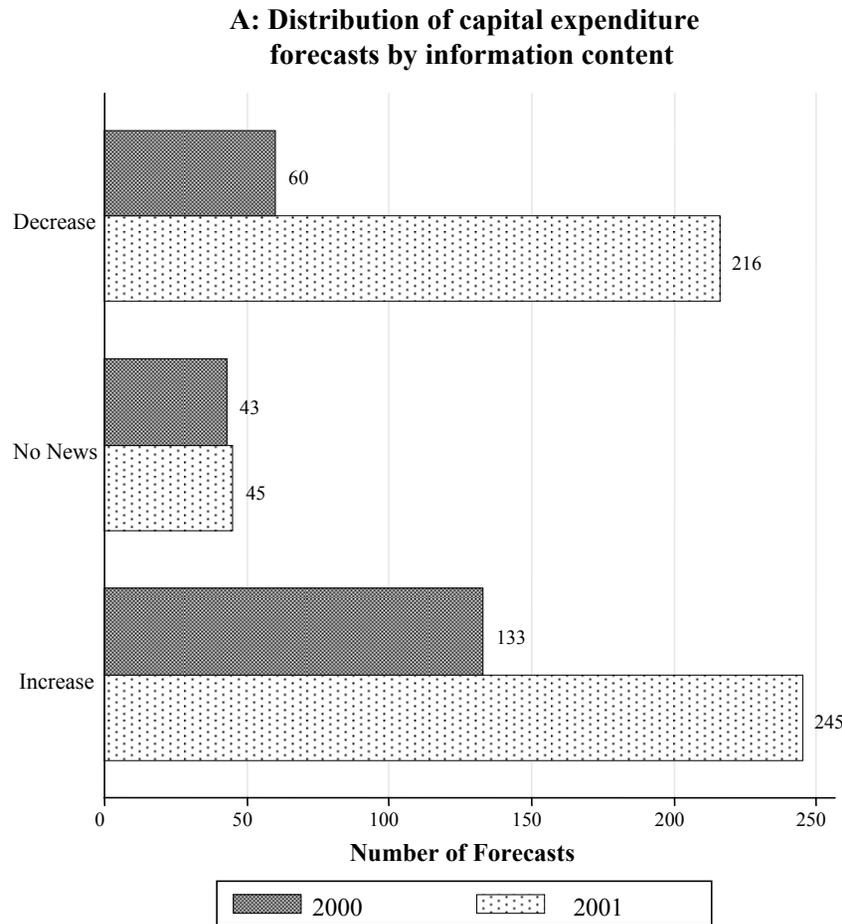


Figure 4

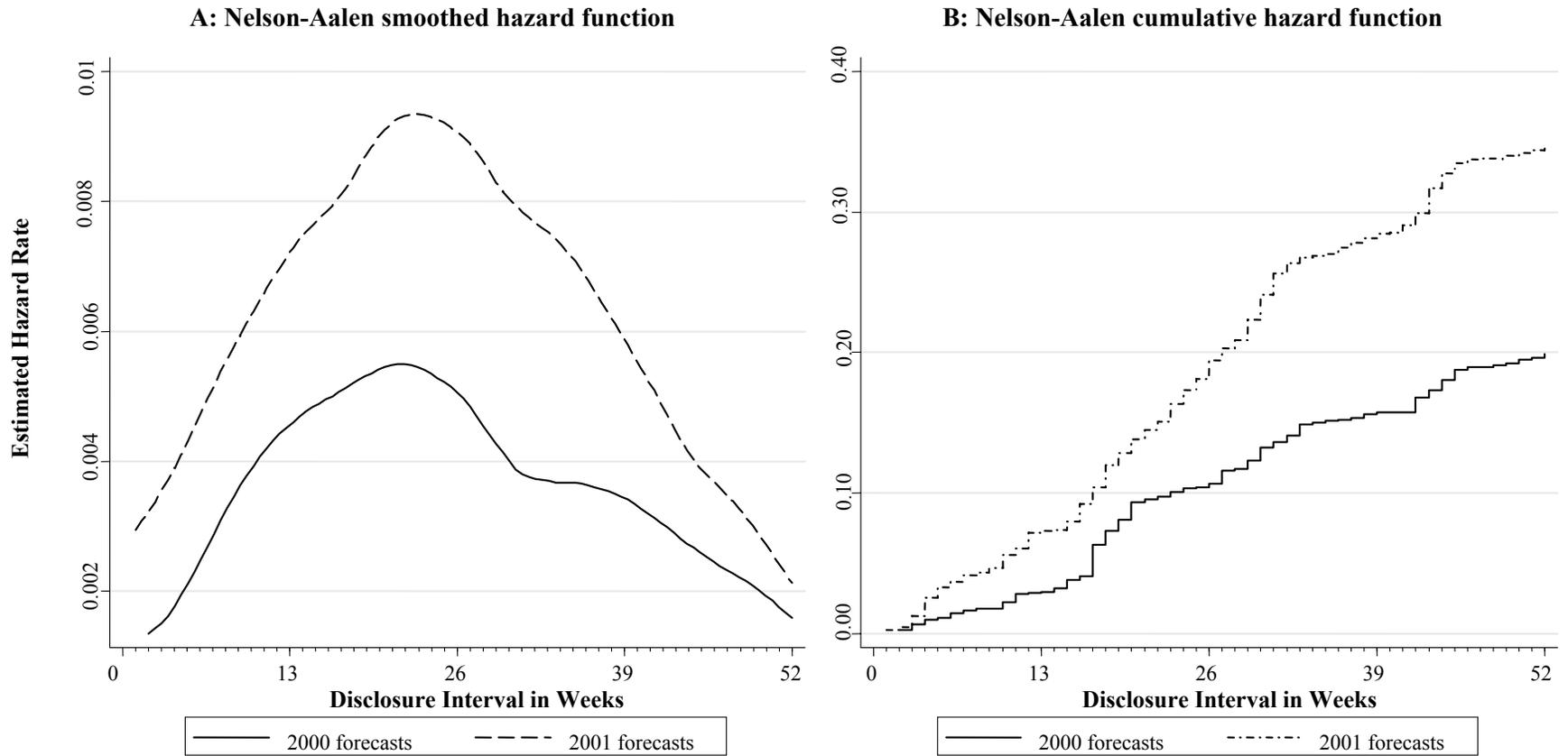
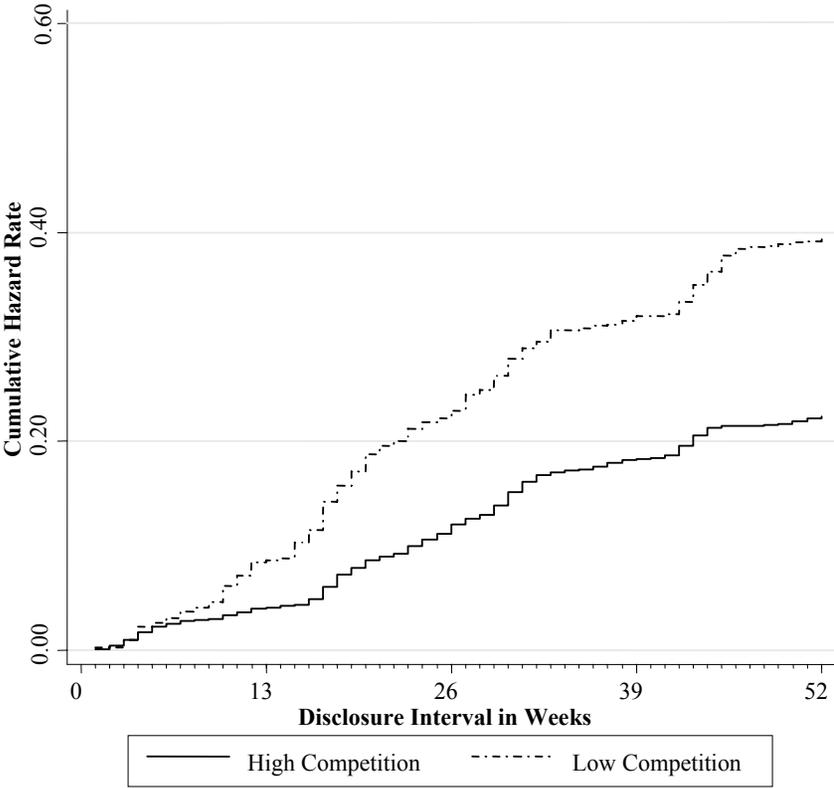


Figure 5

A: Nelson-Aalen cumulative hazard function by level of competition for the full sample



B: Nelson-Aalen cumulative hazard function by degree of capital intensity for the full sample

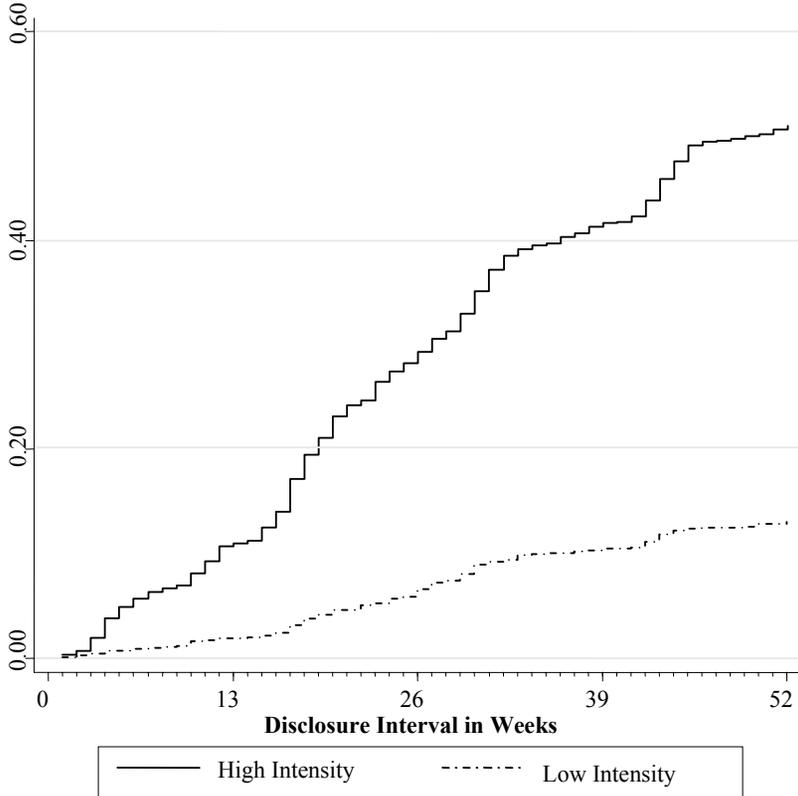


Figure 6

Nelson-Aalen cumulative hazard function by level of competition

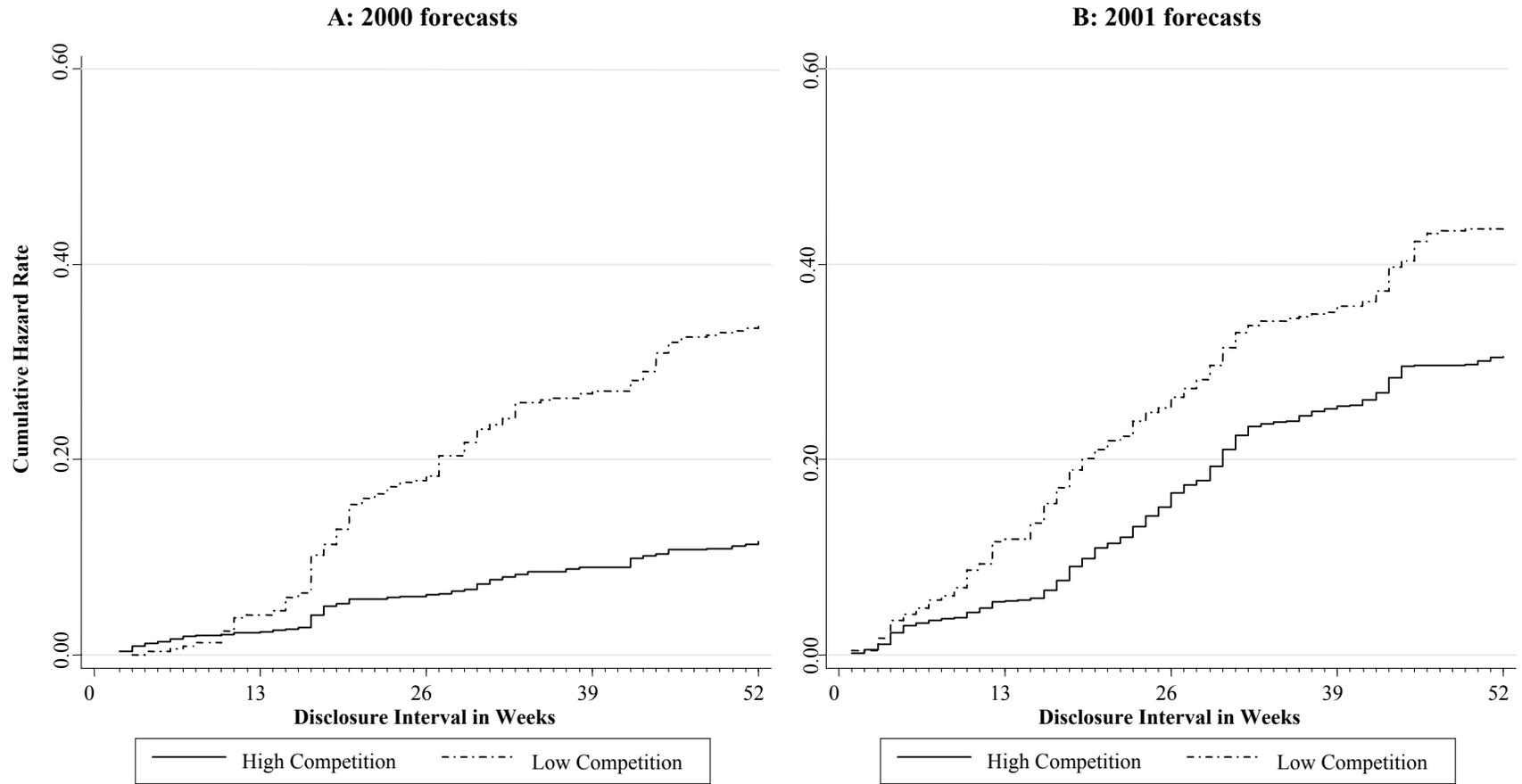


Figure 7

Nelson-Aalen cumulative hazard function by degree of capital intensity

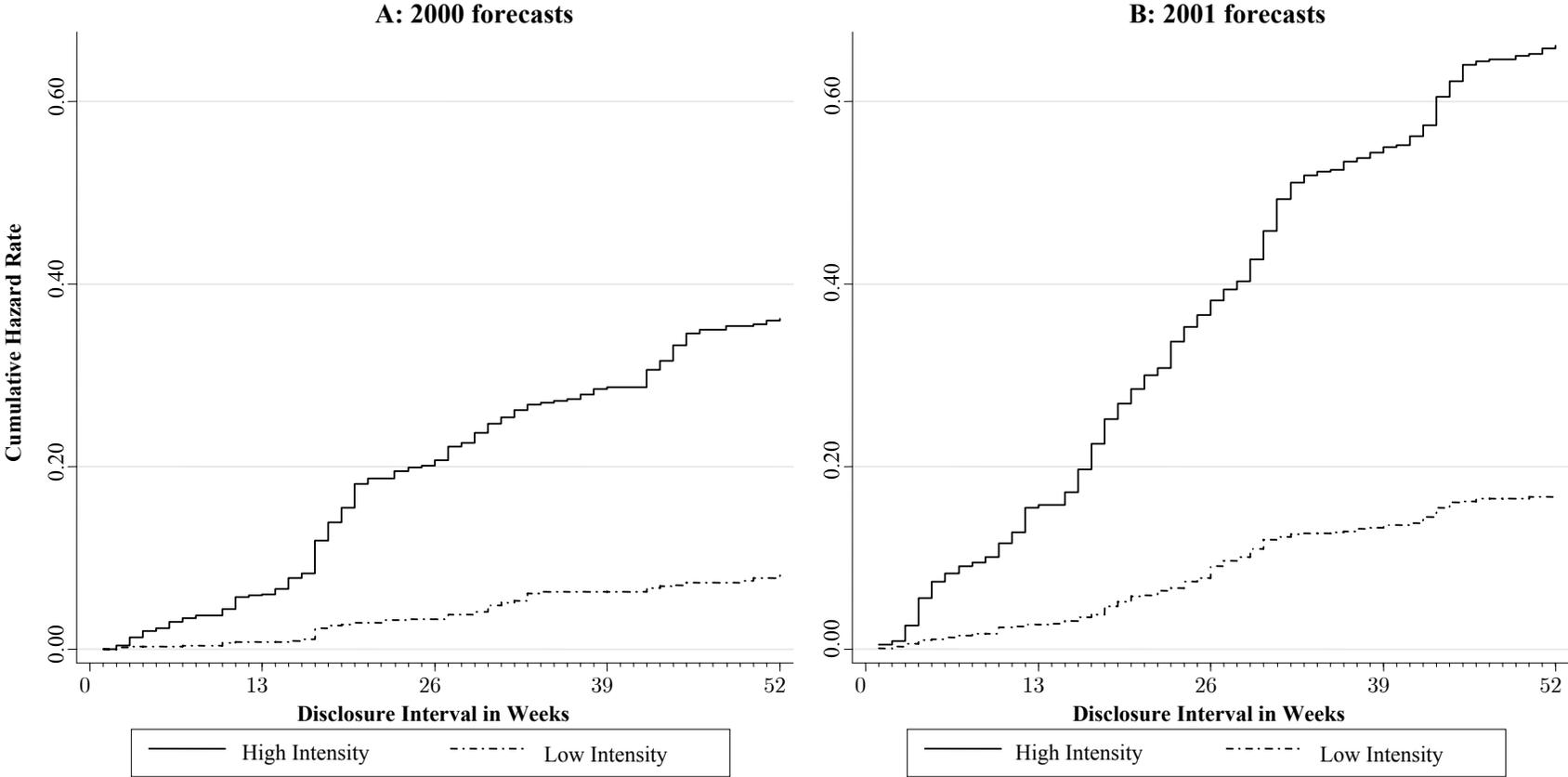
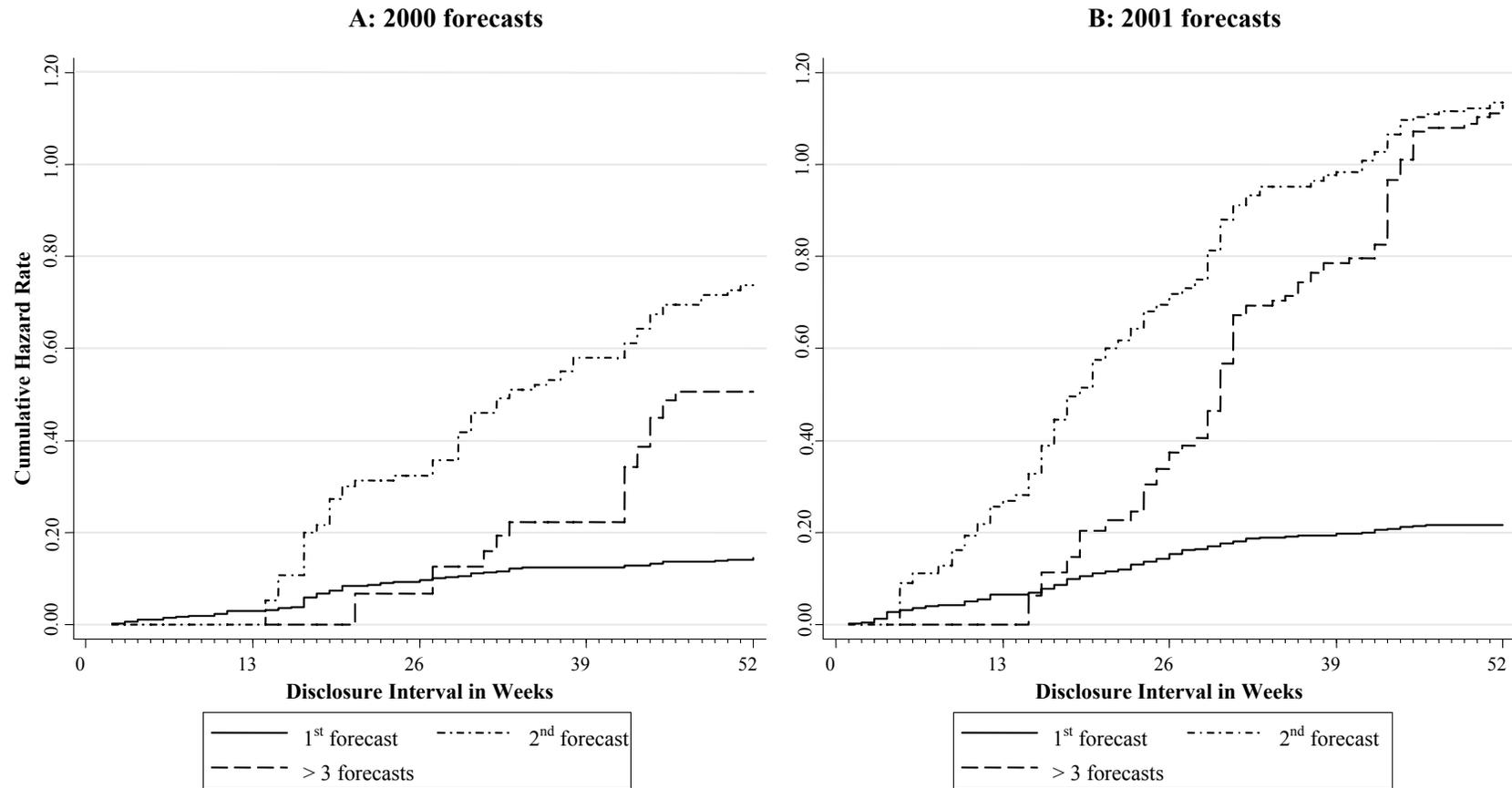


Figure 8

Nelson-Aalen cumulative hazard function by risk pool



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